Quantitative Refinements Of The Magic Formula Value Investment Strategy For Emerging Markets

Laurence E. Day **Quan Nguyen** **Rommel Songco**

ABSTRACT

The 'Magic Formula' is a value investing technique that seeks to identify/rank companies that are undervalued based on certain accounting ratios, with the aim of recommending a basket of the top resulting companies to hold and rebalance annually. This technique has historically been an effective way to beat the market average within the United States, however it has degraded in efficacy in recent years. In this article, we focus on the applicability of the Magic Formula within the BRICS countries (Brazil, Russia, India, China and South Africa).

We find that in all cases, the returns provided by the 'traditional' Magic Formula exceed the underlying national stock markets: in the worst case producing double the returns, and an improvement of an order of magnitude in the best case. We also observe that the addition of a third factor (earnings per share) further increases total returns in all cases, whilst increasing the Sharpe ratio in all cases barring Russia.

Acknowledgements

We'd like to explicitly thank Casper Oakley for his invaluable assistance with data collection for this project.

CONTENTS

1 Introduction 4

2 Theoretical Framework 6
2.1 Magic Formula Research Outside The United States 6
2.2 Magic Formula Research In The BRICS Nations 8

3 Design 10
3.1 Approach 10
3.2 Methodology 10
3.2.1 An Aside: Why The Hang Seng Index? 11

4 Data Collection 12

5 Portfolio Selection 14

6 Performance Measurement 15

7 Results 17
7.1 Brazil 17
7.2 Russia 18
7.3 India 19
7.4 China [Hong Kong] 20
7.5 South Africa 21

8 Statistical Analysis 22

9 Conclusion 23

Appendices 25

A Python TIKR API Scraper 25

B OLS Regressions: Constructed Portfolios vs Market Indices 29
B.1 Brazil 29
B.1.1 Brazil MF Portfolio Statistics 29
B.1.2 Brazil AMF Portfolio Statistics 29
B.2 Russia 30
B.2.1 Russia MF Portfolio Statistics 30
B.2.2 Russia AMF Portfolio Statistics 30
B.3 India 31
B.3.1 India MF Portfolio Statistics 31
B.3.2 India AMF Portfolio Statistics 31
B.4 China [Hong Kong] 32
B.4.1 China [Hong Kong] MF Portfolio Statistics 32
B.4.2 China [Hong Kong] AMF Portfolio Statistics 32
B.5 South Africa 33
B.5.1 South Africa MF Portfolio Statistics 33
B.5.2 South Africa AMF Portfolio Statistics 33

1 Introduction

The ‘Magic Formula’ investment strategy was developed by Joel Greenblatt and described in his 2005 book “The Little Book that Beats the Market” [1]. At it’s core, it represents a technique for identifying quality companies which are undervalued based on two accounting factors: return on capital and earnings yield.

The ‘canonical’ Magic Formula starts by limiting its’ search to the largest 3,500 companies that are publicly listed on US stock exchanges. It ranks those companies in decreasing order based on their return on capital, defined as -

$$ReturnOnCapital = EBIT/(Net\ Fixed\ Assets + Net\ Working\ Capital)$$

- where EBIT stands for ‘earnings before interest and taxes’, or - more commonly - pre-tax operating income. The denominator in the formula above represents the tangible capital employed or the actual capital needed to run the company operations. This includes fixed assets such as property/plants/equipment, less accumulated depreciation, plus the company’s net working capital. Net working capital is computed as current assets minus current liabilities, but excludes cash and short-term debt.

The Magic Formula proposes that - all other things equal - companies with a high return on capital are better investments than companies with a low return on capital. Companies with a higher return on capital earn more relative to the cost of the assets needed to operate the business.

The Magic Formula (henceforth ‘the MF’) technique then ranks the companies based on earnings yield, with 1 being assigned to the stock with the highest earnings yield. Earnings yield is computed as EBIT / Enterprise Value, where enterprise value is computed as the market value of equity plus interest-bearing debt. Earnings yield provides an indication of how much the company is earning relative to the purchase cost of the business. The MF proposes that the higher the earnings yield, the better for the investor, as this indicates higher earnings relative to the purchase price.

The MF then combines the two rankings, and produces a portfolio of 30 stocks with the best combination of return on capital and earnings yield. Greenblatt showed that over a 17-year period from 1988 to 2004, a backtest of the MF produced a compounded annual return of 30.8% [1]. This is significantly higher than the compounded annual return of 12.4% for the S&P 500 over the same period.

Greenblatt’s results for the MF study between 1988 to 2004 are shown in the following table:

Year	**Magic Formula**	**All Shares**	**S&P 500**
1988	27.1%	24.8%	16.6%
1989	44.6	18	31.7
1990	1.7	(16.1)	(3.1)
1991	70.6	45.6	30.5
1992	32.4	11.4	7.6
1993	17.2	15.9	10.1
1994	22.0	(4.5)	1.3
1995	34.0	29.1	37.6
1996	17.3	14.9	23
1997	40.4	16.8	33.4
1998	25.5	(2.0)	28.6
1999	53.0	36.1	21.0
2000	7.9	(16.8)	(9.1)
2001	69.6	11.5	(11.9)
2002	(4.0)	(24.2)	(22.1)
2003	79.9	68.8	28.7
2004	19.3	17.8	10.9
Annual Return	**30.8%**	**12.3%**	**12.4%**

Table 1: 1988-2004 Magic Formula Returns Versus All Shares And S&P500

Since the initial publication of [1], there has been a non-trivial amount of pushback against the core model in both research circles and print media. For the most part, these issues can be divided into one of two camps - namely reproducibility and exposure to drawdown.

For an example of the former, Martin [2] performed a backtest of the strategy that captured all elements except for the capital gains tax optimisation (selling losers before a tax year ends, and winners after a new one starts). When backtesting between July 2003 and December 2015 against the S&P500, the strategy produces an annualised 11.4% against the benchmark's 8.7% - still an improvement of nearly 3%, but is not nearly the margin claimed by Greenblatt. Depending on which subset of data is considered, however, the claim looks more feasible - limiting the timeline to prior to 2007 gives the backtest an annualised return of 26%, in contrast to the benchmark's 18%.

Martin observed that the choice of ranking resulted in a mean Spearman's rank correlation coefficient (which measures the degree to which a ranking lends itself to future returns) of 0.08 - described as 'decent'. He also observes that the strategy they backtested had a drawdown of 57% during the Global Financial Crisis (GFC) of 2007-2010, although this figure must be viewed in light of the fact that the benchmark had a drawdown of 55%, suggesting that there is a significant psychological risk associated with sticking with the MF strategy through thick and thin.

Martin theorises that the GFC acted as a 'fundamental sea change' that reduced the profitability of certain value investing strategies, and posits that a shift towards systematic equity ETFs over the past 20 years may have had some role in reducing arbitrage opportunities such as those 'exposed' by the MF. Martin concludes by suggesting some improvements such as adding a momentum filter (opting to only buy stocks that are ranked highly by the MF when they have positive momentum, to prevent a buyer from buying a cheap stock that's about to get cheaper), or by considering a composite value factor as suggested by the book "What Works On Wall Street" [3] as a more robust alternative to the two single ranking factors used by the MF.

In the same vein of identifying that the recent performance of the MF has been significantly less 'than advertised' in the aftermath of the GFC, Flavelle [4] suggests that changes in the macroeconomic landscape have indirectly led to the 'death' of several value investing strategies. To counter these lower returns, Flavelle suggests add-ons such as a third ranking factor (dividend yield), or by adding an additional filter on the stock universe such as a Piotroski F-score of 6 or above [5].

There are wider concerns regarding the usage of a relative ranking model rather than one that is absolute (i.e. the fact that we are picking companies based on their performance compared to all others in the selected stock universe) - primarily the fact that in a stock market bubble where *all* stock prices are inflated, any selected by the MF would be too: however, in situations such as this, it can be argued that *any* choices made are destined to fail, and the true test is whether the strategy outperforms the wider market recovery in the aftermath of such an event.

2 Theoretical Framework

There are several pieces of work surrounding backtesting of the MF in countries outside of the United States - indeed, globally [6] - and what seem to be a glut of Masters' theses covering the topic for individual markets in the BRICS nations. We present our theoretical framework in the context of a literature review discussing examples of such analyses in non-BRICS countries (to provide an idea of scope: if a country has a significant stock market, it is almost a given that someone has performed a backtest of the MF on it), before isolating studies for each of the BRICS nations in turn.

2.1 Magic Formula Research Outside The United States

In this subsection, we examine some of the results obtained from backtesting the MF strategy in non-BRICS countries outside of the United States.

Backtesting "The Magic Formula" In The Nordic Region

The authors back tested the Greenblatt's Magic Formula in the Nordic Region between January 1, 1998 to January 1, 2008 [7]. They tried to replicate Greenblatt's procedures in portfolio selection, barring a few differences such as rebalancing their portfolio by adding/replacing two stocks in the portfolio every month, as opposed to once a year.

In addition, the authors tested two portfolios in their study. Portfolio I chose the highest ranked stocks based on Greenblatt's canonical definitions of earnings yield and return on capital. Portfolio II, however, modifies the computation of return on capital to EBIT / Capital Employed, where the denominator includes intangible assets such as goodwill, patents, licenses, etc. The authors explain that intangible assets are used by companies in generating their earnings and should be part of the computation of return on capital (Persson & Selander, 2009).

The authors compared the returns of the MF portfolio against the MSCI Nordic benchmark. Over the ten year period, the MF portfolio had a compounded annual return of 14.68% compared to 9.28% for MSCI Nordic. The following table shows the descriptive statistics of results.

	Portfolio I	**Portfolio II**	**MSCI Nordic**
Mean	0.0132	0.0233	0.0102
Median	0.0080	0.0168	0.0104
Standard Deviation	0.0592	0.1040	0.0744
Minimum	-0.1750	-0.1482	-0.1794
Maximum	0.1555	1.0114	0.2389
CAGR	0.1468	0.2609	0.0928
Sharpe Ratio	0.1739	0.1957	0.0973

Table 2: Portfolio Performance versus the MSCI Nordic Index

The results showed that the MF portfolios have a higher return and a higher Sharpe Ratio that the MSCI Nordic benchmark. However, Portfolio II, which was constructed using a modified computation of return on capital which includes intangible assets, outperformed the original MF portfolio.

Magic Formula vs. Traditional Value Investment Strategies in the Finnish Stock Market

The authors compared the performance of Greenblatt's Magic Formula against the most commonly known value investment strategies in the Finnish stock market [8]. The traditional value portfolios are based on the following ratios: a) book value to price ratio (B/P), b) earnings to price ratio (E/P), c) cash flow to price ratio (CF/P), and d) EBIT to Enterprise Value ratio (EBIT/EV). They also tested an augmented MF strategy (MF-CF) by using the cash flow to price ratio as an added factor to earnings yield and return on capital. The authors formed different portfolios consisting of the highest ranked Finnish stocks based on the above factors and tested their performance from 1991 to 2013. The following table shows the performance of the MF and MF-CF portfolios, the traditional value portfolios and the market index:

	MF	**MF-CF**	**B/P**	**CF/P**	**E/P**	**EBIT/EV**	**Index**
Mean Return	19.26%	20.17%	16.74%	19.04%	20.50%	20.57%	13.63%
Standard Deviation	22.63%	22.49%	25.34%	23.81%	22.99%	22.42%	22.96%
Sharpe Ratio	0.641	0.684	0.478	0.601	0.683	0.704	0.380

Table 3: Performance Of MF & MF-Cash Flow Portfolios Relative To The OMX Helsinki 25

The study showed that all the MF and traditional value portfolios beat the market index in terms of higher mean annual returns and Sharpe ratios. However, the portfolio formulated using Greenblatt's MF did not produce the best return nor risk-adjusted return in a small market environment like the Finnish stock market. On the other hand, the pure EBIT/EV and E/P strategies yielded the highest risk-adjusted returns over the study period. The augmented magic formula (MF-CF) using the cash flow to price ratio improved the original MF in terms of absolute and risk-adjusted returns.

Magic Formula Has Its Magic And Momentum Has Its Moments - A Study On Magic Formula And Momentum On The Swedish Stock Market

The authors back tested Greenblatt's Magic Formula investment strategy on the Swedish stock market over a fifteen year period from 2004 to 2018. The purpose of the study was to find out if MF and MF augmented with momentum (MFM) have a higher risk-adjusted return than the benchmark Stockholm OMX30 index. The paper excluded financial companies, such as banks and investment firms, and real estate companies from the study. The MF portfolio consisted of the 20 highest ranked stocks out of a universe of 591 companies. In performing portfolio selection for the MF with momentum, the authors first selected the 40 highest ranked stocks based on MF. Out of the 40 stocks, the 20 companies with the best momentum are selected into the second portfolio. Momentum was calculated as the stock's percentage change in price for the past six months. The following table shows the performance of the MF and MFM portfolios against the benchmark index [9]:

	MF	**MFM**	**OMX30**
Mean Annual Return	18.19%	19.48%	6.95%
Standard Deviation	22.37%	18.01%	16.56%
Sharpe Ratio	0.76	1.02	0.35

Table 4: Performance Of MF & MF-Momentum Portfolios Relative To The OMX30

The results showed that both the MF and MFM portfolios significantly outperformed the benchmark index in terms of absolute returns and risk-adjusted returns as measured by the Sharpe ratio. The study also showed that the MF combined with momentum outperformed the original MF portfolio in absolute and risk-adjusted basis.

Does Magic Formula Investing Work In Hong Kong Stock Market?

A common extension to the MF investing is the combination with other fundamental or value factors, among which Fama-French three factor model is a well-known example [10,11]. Fu and Xia [12] have explored this approach in an effort to join the train of the new researches that look for new common risk factors. The authors defined two variations of the MF -

$$MF1 = \frac{EBIT}{Net\ Working\ Capital + Net\ Fixed\ Assets} \qquad MF2 = \frac{EBIT}{Total\ Assets - Current\ Liability}$$

- and then adopted a similar approach to the Fama-French papers with the inclusion of the MF factors.

The methodology involved investigating different single-sorted and double-sorted portfolios to evaluate the excess performance and performing time-series and Fama-Macbeth regression [13] on the compound risk factors to measure the explanatory power and risk premium. The author concluded that when ranked by the value of magic formula, the top 30% had annualized return of 20.26% while the bottom 30% had annualized return of 5.65% for the large stocks. For the small stocks, the top stocks' return exceeded the bottom stocks' return by 6.04% annually. Another interesting finding is adding MF1 boosted the adjusted R-squares of the time series regressions by 1% as compared to the standard Fama-French model, together with a significant beta for MF1. The Fama-MacBeth regressions further confirmed that the risk premium for MF1 was also significant at a value of 0.19.

Magic Formula Investing In The Benelux

Researchers [14] verified the effect of the Magic Formula in the Benelux (Belgium, Netherlands and Luxembourg) stock market over the period between 1995 and 2014. The experiment used a slightly different formulation of ROIC and EY with a compounded ranking computed from individual rankings of each factor to evaluate the stocks. An annually re-balanced equal-weighted portfolio is formed using the top 10 stocks. The result confirmed an excess return of 7.7% and negligible excess risk over the market portfolio. The beta recorded was 0.98, which is very close to 1, further confirms the fact of negligible excess risk. The author has also raised a question about the rationale of the MF investing and the relation to behavioral finance, which could be an intriguing topics for future research.

2.2 Magic Formula Research In The BRICS Nations

In this subsection, we take a closer look at how MF investing fares in the market context of BRICS nations.

Starting with India, an experiment [15] showed that MF investing beat NIFTY 50, NIFTY 500, NIFTY Midcap 100 and NIFTY Smallcap 100 over the past 18 years in a relatively consistent manner. Specifically, an annually re-balanced portfolio of 25 best stocks selected using MF formula generated a CAGR of 35.4% as compared to 10-15% CAGR of the aforementioned benchmarks.

The author also explored further with the robustness of the MF. An important quality of a good alpha is the classification power, where stocks with higher alpha values would have higher returns. Top 500 stocks were ranked by MF values and divided into 20 groups. The observed performance confirmed the expectation of good classification power:

	CAGR 2002-2020	CAGR 2008-2020
Group 1	35.4%	20.2%
Group 5	25.1%	11.8%
Group 10	19.6%	11.5%
Group 15	20.9%	9.5%
Group 20	12.5%	3.2%

Table 5: Compound Annual Growth Rate Of Top-Ranked (By MF) Indian Stocks

One argument against the robustness of the above alpha is the divergence between backtesting and real trading due to market impact, which could be amplified if the selected stocks have a low market capitalisation or average dollar volume. The author provided a counter-argument by showcasing the market-cap composition of the selected portfolio and further updating the universe to large-cap stocks. One may argue a more suitable measure would be average dollar volume. The article also experimented with potential improvements to the models like applying a Return On Capital Employed filter, which under-performed the standard MF model.

	CAGR 2002-2020	CAGR 2008-2020
Portfolio Top 25	35.4%	20.2%
Portfolio Top 25 Large Cap	23.7%	13.4%
Portfolio with RoCE Filter	-	17.9%
Nifty 50	12.7%	7.1%
Nifty 500	13.5%	7.3%
Nifty Midcap 100	14.6%	7.7%
Nifty Smallcap 100	10.6%	1.6%

Table 6: Compound Annual Growth Rate Of Various Indian Stock Portfolios

Studies [16] have also shown evidence of the MF working in the South African market. The research looked at an universe of market-cap greater than 100 million ZAR with a non-financial-sector filter over a period of 10 year from 2005 to 2015. It went beyond the boundary of strategy reaffirmation to find optimal values for a set of parameters, namely portfolio size and holding period, that will maximize the performance for different investor risk appetites:

Risk Appetite	Holding Period	Portfolio Size	Explanation
Risk-averse	5 years	20 shares	Lowest volatility
Risk-seeking	1 year	10 shares	Highest geometric return
Risk-neutral	2 years 6 months	10 shares 15 shares	Highest risk adjusted return

Table 7: Statistics Of Various Risk-Appetite MF Portfolios In The South African Market

On a statistical basis, the experiment confirmed that the MF does influence the return but failed to prove that there is a significant out-performance of the MF portfolio over JSE ASLI, which is a benchmark proxy for the market. Also the tuning of parameters may be argued to be a process of over-fitting and the selected parameters may not perform well out of sample.

Many authors took a similar approach of fine-tuning the parameters of the standard MF strategy when analyzing the effectiveness of the strategy on other markets. Particularly for the Chinese A-shares market, the author [17] also looked at holding period and market cap and further explored the effect of depreciation and amortization, introduction of PE * PB and different mixing weights for the factors.

The result stated that the return increases with longer holding period and smaller market cap (at the cost of higher risk and market impact). The research also found that using EBITDA as an alternative for EBIT and applying a filter ensuring that PE * PB $\leq$ 30 greatly boosted the returns while controlling for risk. The author advocated the adoption of the MF strategy in the Chinese A-shares market because of its simplicity and superiority.

Researchers have also arrived at a similar conclusion that the MF investment strategy outperforms the market benchmark for the Brazilian [18] and Russian [19] markets over the investigated period. For the Brazilian market, despite the observable empirical result, there was insufficient statistical significance to conclude that the performance was attributed to an actual alpha. The author adopted the CAPM as a proxy to compute the theoretical alpha and found that "only the 0.98% alpha of top 5 portfolio resorted every 12 months regressed on Ibovespa could achieve a 90% level of significance while all other portfolios alphas were not significant at any meaningful level".

In the Russian case, the CAPM was also used to evaluate the risk-adjusted return for the MF strategy in the Russian market but did not take deeper dive into the statistical aspects of the result. The showcased portfolio of 30 stocks had an annualized return of 24.75% as compared to an annualized return of 14.49% of the market benchmark.

3 Design

The objective of any equity investment strategy is to outperform the market index or market average consistently and on a risk-adjusted basis. Simply matching the performance of the market index can be achieved in a straightforward manner by buying an ETF that replicates the stock market index. Value investing - the crux of this paper - has historically been one of the most popular and successful investment strategies for beating the market average, with many different forms and techniques.

3.1 Approach

This project aims to apply and back test Greenblatt's Magic Formula investment strategy in the equity markets of the BRICS nations (Brazil, Russia, India, China and South Africa) over a ten year period from 2010 to 2019. The approach of this project is to replicate the strategy in terms of the stock selection criteria in portfolio creation and the computation of factors used in ranking companies. The project then measures the performance of the MF portfolios, which are re-balanced every year during the ten year period. The project aims to determine whether these portfolios created using the Magic Formula can outperform their respective benchmark indices over the course of a decade.

The formation of the MF portfolio is based on the combination of two factors: the return on capital and the earnings yield. The ranking based on return on capital favors companies which are more profitable because they earn more on their tangible capital. The ranking based on earnings yield favors undervalued companies because they have higher earnings relative to the stock price. The combination of the two aims to select 'good' companies at bargain prices.

A strength of the MF technique is that the two factors used in the rankings are comparable across different companies. The earnings term used - EBIT - is independent of a company's debt levels and tax rates, and the earnings yield (EBIT/EV) is likewise unaffected by such differences across companies. In contrast, the traditional earnings to price ratio (E/P) is influenced by a company's debt level and tax rate.

Greenblatt's computation of return on capital (EBIT / Tangible Capital) has a bias toward companies that have relatively small net fixed assets but may have large intangible assets. Greenblatt's justification is that tangible capital alone needs replacement from time to time to continue business operations in the future, and that as a result, return on tangible capital is more indicative of a company's return on capital in the future.

What is missing in Greenblatt's Magic Formula is an indication of the trajectory of a company's business in terms of growth. It is possible that the MF may include value traps where the stock still has a relatively high trailing twelve-month return on capital and is cheap based on a high earnings yield but the earnings per share (EPS) is erratic or declining over time.

3.2 Methodology

We aim to develop an investment strategy based on Greenblatt's Magic Formula applied within the BRICS countries, which is a diversified representation of emerging market economies. We shall backtest the MF for each member country, comparing performance of the MF portfolio against that country's stock market index over a ten year period from 2010–2019.

For each country, the MF portfolio shall be selected from among the components of a major stock index, ensuring that the stocks in the MF portfolio have sufficient liquidity. In addition, this method aims to outperform the stock market index using blue chip stocks that are a subset of that index. On paper, this appears to be a less risky strategy to outperform the market index, a point subject to verification during our research. In each case, our constructed portfolios will consist of the stocks ranked within the first quartile from that market.

Following Greenblatt's method, we shall exclude financial stocks such as banks, insurance and investment companies from consideration in the MF portfolio.

For each year from 2010 to 2019, we will consider the stock market index components for each country. For each stock component, we will compute the trailing twelve month return on capital and earnings yield in accordance with Greenblatt's Magic Formula (i.e. for the year 2010, these values are calculated using values available from financial statements for 2009).

The return on capital is computed as -

$$EBIT/(Net\ Fixed\ Assets + Net\ Working\ Capital)$$

- where EBIT is earnings before interest and taxes, or 'operating income'. Net fixed assets is gross property, plant and equipment minus accumulated depreciation. Net working capital is computed as current assets minus current liabilities minus cash and cash equivalents plus short-term debt.

Earnings yield is computed as -

$$EBIT/Enterprise\ Value$$

- this is the stock's market capitalization plus preferred stock plus debt minus cash and cash equivalents.

We then rank the companies based on return on capital from highest to lowest, with 1 being assigned to the stock with the highest return on capital. Next, we rank the stocks based on earnings yield from highest to lowest, with 1 being assigned to the stock with the highest earnings yield. We then take the average of the two ranks to determine the final ranking, selecting for our portfolios the companies within the top quartile of this ranking.

In addition, we shall create an augmented MF portfolio for each country by adding an additional factor that computes the percentage change in earnings per share where earnings is represented by EBIT. To create this second portfolio, we take the top half of the MF ranking, then rank these stocks according to the percentage change in earnings per share. Our augmented MF portfolio will consist of the top half of this group, comprising those with the highest percentage change in earnings per share.

The stocks in the MF and augmented MF portfolios are assumed to have equal weightings, and are assumed to be held from the start of April and re-balanced at the end of March the following year by repeating the above calculations. To avoid survivorship bias, in the event that any company contained therein ceases trading during a given year, we will consider their last trading price as the price of that company at year-end.

The performance of the MF and augmented MF portfolios shall be measured on both an absolute and risk-adjusted basis. The performance of these portfolios shall be compared against the performance of their respective stock market indices. Absolute performance will be measured in terms of the compounded annual return from the beginning of April 2010 until the end of March 2019. Risk-adjusted performance shall be measured using the Sharpe ratio.

Our project's scope of applying and testing Greenblatt's Magic Formula for all BRICS countries individually, using blue chip stocks from the market index to create the MF portfolio, and adding an additional factor using EPS, is unique. To the best of our knowledge, this is the first research of its kind with the aforementioned parameters to be undertaken.

3.2.1 An Aside: Why The Hang Seng Index?

The eagle-eyed will have noticed that we are referring to the Hang Seng Index as a national stock market index for China, whereas in truth it is a Hong Kong institution. Our reasoning for this is that the Chinese stock market has limited exposure to foreigners - whilst investors can indeed gain exposure to Chinese companies by investing in the A-shares market or various ETFs, the ability to invest in specific companies is constrained. To this end, we treat Hong Kong as a 'proxy' for China (notwithstanding any debate about the "one country, two systems" principle currently in place), and thus use a Hong Kong index in lieu - henceforth referring to 'China' as 'China [HK]' to make the substitution clear.

4 Data Collection

The first step is to collect historical index membership of each index between 2010 and 2019, and augmenting this data with pricing and financial statement data for each constituent. In this section we will discuss the various phases undertaken to go from database queries of index members to concrete rankings for the Magic Formula.

Whilst the *current* constituents of a national stock index are generally easy to find - more often than not available on the website of the index itself -, historical membership data is generally only accessible through the usage of a specialised database. In this instance, we obtained our lists of constituent companies via Bloomberg Terminal [20], querying the composition of the indices in question as of the 1st of January on each year.

We note despite the names of some of the indices suggesting that there should be a specific number of stocks contained within (i.e. the FTSE/JSE 40 ‘should’ contain 40 stocks, or at least be restricted to 40 companies, to account for the inclusion of regular and preference shares, for example). In practice this is not the case, varying (often quite significantly) year on year.

After collecting these membership lists, we filtered out any stocks that are listed under the ‘Financials’ sector on Bloomberg website, per the canonical formulation of the magic formula. Whilst a ‘true’ interpretation of the magic formula would also exclude utilities stocks, we opted to retain them in our research, as to do otherwise would result in us dropping under 20 stocks from which to choose per year in some cases, potentially skewing the odds of selection in favour of companies that would otherwise not be included simply because they have a presence on TIKR and others do not.

Thereafter, we confirmed whether the remaining stocks appeared on TIKR, a research platform aiming to “bring institutional-quality investment research tools to a broader audience” [21] that provides historical financial statements for companies (which are key to determining magic formula rankings). TIKR is currently - at the time of writing - in beta and permitting free sign-ups from the public[1]. If we could not find a TIKR key for a given company, we dropped it from consideration.

Instead of performing all of the requisite calculations for determining MF ranking by hand (i.e. browsing financial statements for relevant figures and keeping track in a spreadsheet), we produced a Python script that scrapes the TIKR website for the full dictionary of financial values associated with a given company for all years that data is available in order to automate the work for us. The (relatively short) code for this is available in Appendix A, and can also be found at the following GitHub repository: `https://github.com/ng0021an/magic`.

Regarding price data, we designed our Python script to retrieve the price data for the day on which financial records were filed - these dates form the header row for the balance sheets and income statements of a company in their ‘Financials’ section on TIKR, as illustrated by a sample screenshot for AAPL below:

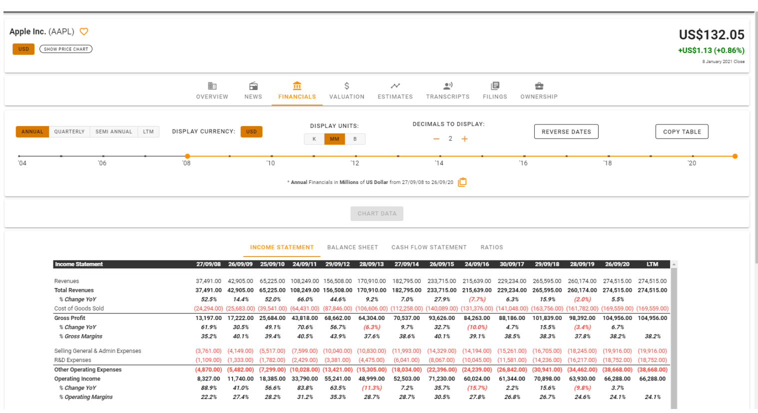

Fig. 1. Example Of TIKR’s Financial Tab, Displaying AAPL’s Income Statements

[1] We chose to make use of TIKR for financial data rather than continue to make use of Bloomberg Terminal, in order to determine whether the MF strategy can be implemented using data that is freely available to the wider public, if they knew the current composition of an index.

We observed during this phase that whilst TIKR had financial statements for every year (and stock) which we were interested in examining, this completeness did not apply to pricing data. This was particularly true of both Russia and Hong Kong (respectively the MOEX and Hang Seng indices): in the former case, the MOEX replaced a previous index - the MICEX - which may go some way to explaining the spottiness of data, whereas for Hong Kong stocks, it appears that price data is more simply sporadic than for other countries, meaning that often searching for price data on a specific date would return null values (although we note that after 2016, pricing data was generally very reliable).

In these cases, we made use of Yahoo! Finance [22] to retrieve the price - if available - and manually calculated the yield for a company[2] - given the relatively small number of cases where this was required, it was considered to be more of an effort to modify the script to search for the chronologically-closest price as a stand-in.

If we were unable to find pricing data for a stock in a given year on either TIKR or Yahoo!, we dropped the company from consideration for the year in question.

At the conclusion of our data collection and cleaning stage, we were left with a restricted subset of each year's index composition from which to draw our portfolio. The table below illustrates *how many* stocks were left in our 'cleaned' lists: i.e. how many candidate stocks were under consideration each year for inclusion -

Country	**'10**	**'11**	**'12**	**'13**	**'14**	**'15**	**'16**	**'17**	**'18**	**'19**
Brazil	38	39	40	47	51	51	45	40	46	53
Russia	22	23	24	41	42	40	42	42	39	37
India	39	37	38	38	37	38	39	40	39	38
China [HK]	30	32	34	36	36	36	36	36	37	38
South Africa	24	27	28	28	28	26	24	29	25	26

Table 8: Number Of Candidate Stocks For Portfolio Selection Post-Data Collection/Cleaning

[2] We were somewhat lucky in this regard, as even if price data for a company was missing, the financial statements were enough for the Python script to determine the ROC and EPS-shift, meaning that we only had to calculate a single data point per company per year.

5 Portfolio Selection

Using the normalised historical financial statement data collected in the previous step (either via our Python TIKR scraper or manually calculated where data is missing or sporadic), we compute the return on capital, earnings yield and percentage change in earnings per share for each stock comprising the national indices of the BRICS nations. We then select those companies ranked in the top quartile by the Magic Formula system to be the members of our MF portfolio. To construct the augmented Magic Formula portfolio, we consider the top half of the rankings (i.e. all stocks selected as members of the MF portfolio along with the second quartile) and rank these according to their annual percentage change in earnings per share, and select the top half of this second ranking.

To illustrate the portfolio selection process, consider the following (mock) table:

Name	ROC	ROC #	Yield	Yield #	MF #	EPS	EPS #
A	10%	2	10%	1	1.5	10%	1
B	9%	3	9%	2	2.5	5%	4
C	12%	1	8%	3	2	7%	3
D	7%	4	7%	4	4	9%	2
E	6%	5	6%	5	5	4%	-
F	5%	6	5%	6	6	4%	-
G	4%	7	5%	6	7	2%	-
H	3%	8	4%	7	8	3%	-

Table 9: An Example Of Selecting MF/AMF Portfolio Members Via Ranking

Based on the dummy values above, we select companies **A** and **C** to be the two companies in our constructed MF portfolio (as the top quartile of a set of 8 companies is 2), whereas we select companies **A** and **D** for our augmented MF portfolio. Even though company **C** has a higher magic formula rank than **D**, the latter has a higher earnings per share for that year, and thus wins out. Note that the magic formula ranking is calculated as an average of the ROC and Yield rankings, whereas the EPS ranking correlates directly to their ordering.

Spreadsheets containing all workings are included in the GitHub repository `https://github.com/ng0021an/magic`.

The process of selecting the magic formula and augmented magic formula portfolios for a given year is based on the annual financial statements of the prior year. These annual financial statements are released to the public sometime during the first quarter of the following year. Thus, we make the assumption that using the annual financial statements of the prior year, the MF and augment MF portfolios are only determined at the end of March. The one-year holding period for the MF and augmented MF portfolios start on April 1 and end on March 31 of the following year. The MF and augmented MF portfolios are re-balanced at the end of March every year by repeating the above-mentioned process.

6 Performance Measurement

Assuming equally-weighted portfolios, we measure the annual percentage returns of the magic formula and augmented magic formula portfolios for each one-year holding period between 2010 and 2019 inclusive. The return of each stock in the MF and augmented MF portfolios is computed as the total return of the stock from the beginning of the holding period (April 1) until the end of March of the following year including all dividends received during the period. All stock prices, dividends and returns are measured in the local currency. For the stock indices we are measuring against, we simply consider the baseline change in the index value between April 1 and March 31 of the following year.

We also measure the *total* returns across the decade, as well as three descriptive statistics: the compound annual growth rate (CAGR) - the required annual rate of return to achieve the final result -, the standard deviation - a measure of the volatility of the underlying - and the Sharpe ratio. Although the first two are somewhat obvious, we remind ourselves that the Sharpe ratio is defined as the average return in excess of the risk-free rate with regards to the volatility of the underlying [23].

As such, the Sharpe ratio measures the performance of our constructed portfolios versus the market indices on a risk-adjusted basis. It is defined as -

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

- where R_p is the return of a portfolio, R_f is the risk-free rate, and σ_p is the standard deviation of the portfolio's return.

In order to calculate Sharpe ratios, we need to determine what constitutes R_f for each of these countries. To this end, we considered the yield of 90 day bonds as of the end of March 2020 from the treasuries of each nation respectively [24]. These 'risk-free rates' - as so defined - are:

Country	Risk-Free Rate
Brazil	3.415%
Russia	5.94%
India	4.274%
China [HK]	0.626%
South Africa	4.256%

Table 10: Risk-Free Rates

We also factor in the impact of transaction costs on the performance of the MF and augmented MF portfolios. To this end, we shall include explicit costs pertaining to the fees/taxes that are charged for equity trading activities in the BRICS countries, including commissions, costs - concerning settlement, clearing, transfer et al - and the capital gains tax. The capital gains tax is a tax charged on the profits realised upon closing a stock position. We assume this to be from the point of view of a foreign or non-resident investor. The following table summarises the stock trading transaction costs within BRICS:

	Brazil	Russia	India	China [HK]	South Africa
Commission	0.75%	0.1%	0.5%	0.2%	0.5%
Fees	0.1206%	0.01%	0.2088%	0.1097%	0.3252%
Capital Gains Tax	15%	30%	10%	0%	10%

Table 11: Transaction Costs

Besides explicit transaction fees, Transaction Cost Analysis (TCA) also includes slippage or market impact analysis. The universes used for the portfolio constructions are the market index components, which should have large market capitalisations and hence large average dollar volume. Market impact for stocks with high liquidity are generally controllable unless the size of the managed assets reach certain levels where transactions may dramatically move the market.

This can be derived from the classic square-root model, which is sometimes referred to as the square-root law -

$$\Delta P = \text{Spread Cost } + \alpha\sigma\sqrt{\frac{Q}{V}},$$

- where α is a constant factor, σ is daily volatility, Q is the size of the order and V is daily volume.

For hedge-funds, the Assets Under Management (AUM) metric tends to be controlled at a reasonable level so that funds can be effectively managed and market impact can be minimised. For mutual funds and other bigger sized funds, certain indices are used as benchmarks, such that - if the transactions are big enough to move the whole indices - fund managers may still beat the indices over the long run. This in some sense is similar to ”front loading”, a technique where fund managers can ”cheat” certain execution benchmarks like Volume Weighted Average Price (VWAP) by benefiting from excessive market impact at the beginning of order executions [25]. Other benchmarks like Implementation Shortfall (IS) may be harder to cheat, but at the same time may not give a full picture of how well the execution algorithm is faring against the general market, which may be inappropriate for passive fund managers.

7 Results

The results of our analysis are as follows:

7.1 Brazil

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	25.35%	23.71%	-9.67%	5.94%	9.91%	-6.65%	35.95%	29.9%	19.62%	-6.3%
AMF	26.04%	22.71%	-5.8%	3.91%	11.59%	-5.81%	32.54%	31.68%	15.66%	-4.86%
BOVESPA 50	-1.91%	-4.19%	-4.92%	-2.81%	2.31%	-2.86%	28.18%	32.08%	10.57%	-25.64%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	201.38%	11.66%	16.52%	0.4994
AMF	205.63%	11.82%	15.32%	0.5486
BOVESPA 50	20.16%	1.85%	16.88%	-0.0925

Table 12: Brazil Magic Formula Results Before Transaction Costs

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	19.88%	18.50%	-11.33%	3.53%	6.87%	-8.34%	28.81%	23.71%	15.05%	-7.98%
AMF	20.46%	17.66%	-7.49%	1.81%	8.29%	-7.50%	25.94%	25.21%	11.72%	-6.56%
BOVESPA 50	-1.91%	-4.19%	-4.92%	-2.81%	2.31%	-2.86%	28.18%	32.08%	10.57%	-25.64%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	115.52%	7.98%	14.49%	0.3150
AMF	120.13%	8.21%	13.34%	0.3594
BOVESPA 50	20.16%	1.85%	16.88%	-0.0925

Table 13: Brazil Magic Formula Results After Transaction Costs

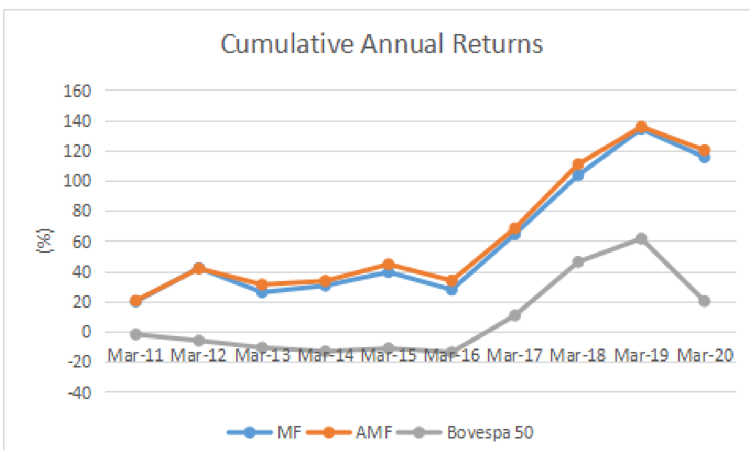

Fig. 2. Brazil Cumulative Annual Returns After Transaction Costs

Both of our constructed portfolios significantly outperform the Bovespa index, with total returns about 5 times greater in both cases, and a large increase in the Sharpe ratio for both. The volatility in both cases is - notably - *lower* than that of the main index. However, we note that the augmented magic formula portfolio (AMF) outperforms the 'vanilla' MF portfolio on both metrics.

7.2 Russia

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	26.60%	1.76%	8.67%	13.18%	43.02%	62.53%	32.64%	24.09%	8.77%	23.57%
AMF	29.29%	-11.18%	12.6%	17.67%	52.13%	67.21%	35.23%	18.01%	14.96%	13.95%
MOEX 50	25.06%	-16.34%	-5.19%	-4.82%	18.76%	15.06%	6.67%	13.78%	9.96%	0.47%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	714.87%	23.34%	18.27%	0.9525
AMF	709.14%	23.25%	22.18%	0.7806
MOEX 50	73%	5.63%	12.72%	-0.024

Table 14: Russia Magic Formula Results Before Transaction Costs

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	18.45%	1.08%	5.91%	9.06%	29.93%	43.57%	22.67%	16.69%	5.98%	16.33%
AMF	20.32%	-7.97%	8.66%	12.20%	36.30%	46.84%	24.48%	12.44%	10.30%	9.60%
MOEX 50	25.06%	-16.34%	-5.19%	-4.82%	18.76%	15.06%	6.67%	13.78%	9.96%	0.47%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	355.22%	16.36%	12.77%	0.8161
AMF	357.20%	16.42%	15.51%	0.6754
MOEX 50	73%	5.63%	12.72%	-0.024

Table 15: Russia Magic Formula Results After Transaction Costs

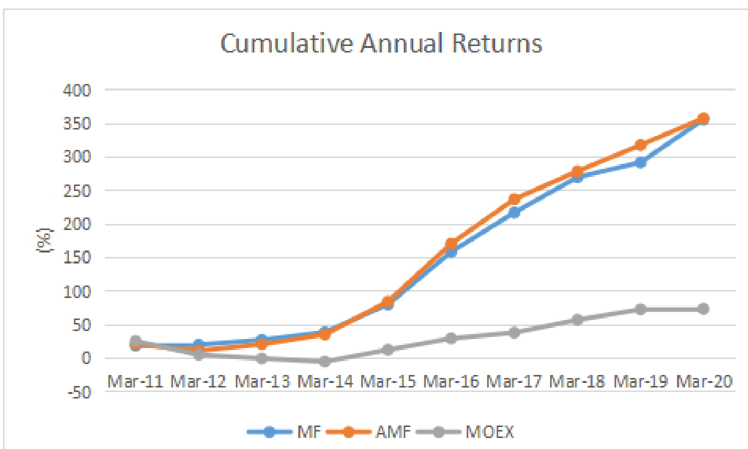

Fig. 3. Russia Cumulative Annual Returns After Transaction Costs

Similarly to the Brazil case above, both of our constructed Russian portfolios outperform the MOEX index by 5 times returns-wise, with concomitant significant increases in the Sharpe ratio. In contrast, however, the volatility is higher for both of our portfolios when compared to the underlying index.

7.3 India

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	17.37%	4.69%	2.59%	34.02%	33.73%	-0.42%	24.15%	11.08%	5.86%	-30.33%
AMF	17.98%	1.4%	10.63%	34.25%	39.73%	1.24%	23.30%	21.66%	5.63%	-32.84%
Nifty 50	11.14%	-9.23%	7.31%	17.98%	26.65%	-8.86%	18.55%	10.25%	14.93%	-26.03%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	128.8%	8.63%	18.94%	0.2299
AMF	167.58%	10.34%	20.56%	0.2952
Nifty 50	63.79%	5.06%	16.1%	0.0487

Table 16: India Magic Formula Results Before Transaction Costs

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	14.24%	2.91%	1.04%	29.12%	28.86%	-1.84%	20.30%	8.63%	3.96%	-31.53%
AMF	14.80%	-0.02%	8.23%	29.33%	34.28%	-0.18%	19.54%	18.08%	3.75%	-34.03%
Nifty 50	11.14%	-9.23%	7.31%	17.98%	26.65%	-8.86%	18.55%	10.25%	14.93%	-26.03%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	80.49%	6.08%	17.70%	0.1022
AMF	108.02%	7.60%	19.22%	0.1730
Nifty 50	63.79%	5.06%	16.1%	0.0487

Table 17: India Magic Formula Results After Transaction Costs

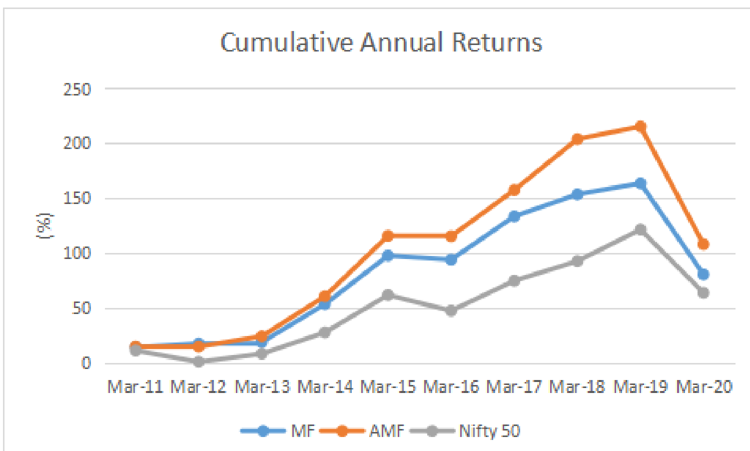

Fig. 4. India Cumulative Annual Returns After Transaction Costs

Of all of the BRICS countries we examined, India was the 'closest' when comparing performances between our constructed portfolios and the indices that their components were drawn from. However, both the MF and AMF portfolios still outperform the Nifty 50 index on absolute and risk-adjusted returns.

7.4 China [Hong Kong]

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	15.85%	-4.45%	1.09%	2.51%	12.91%	-9.22%	6.88%	26.16%	4.42%	-8.84%
AMF	19.49%	-2.98%	18.61%	2.02%	13.46%	-5.13%	12.37%	31.63%	-1.51%	-11.87%
Hang Seng	10.77%	-12.63%	8.48%	-0.67%	12.41%	-16.56%	16.05%	24.81%	-3.46%	-18.75%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	50.9%	4.2%	11.23%	0.3182
AMF	93.84%	6.84%	13.6%	0.4571
Hang Seng	11.13%	1.06%	14.8%	0.0294

Table 18: China [Hong Kong] Magic Formula Results Before Transaction Costs

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	15.18%	-5.06%	0.46%	1.88%	12.25%	-9.82%	6.24%	25.46%	3.78%	-9.43%
AMF	18.81%	-3.59%	17.93%	1.40%	12.80%	-5.74%	11.71%	30.91%	-2.13%	-12.46%
Hang Seng	10.77%	-12.63%	8.48%	-0.67%	12.41%	-16.56%	16.05%	24.81%	-3.46%	-18.75%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	41.97%	3.57%	11.20%	0.2625
AMF	82.49%	6.20%	13.56%	0.4111
Hang Seng	11.13%	1.06%	14.8%	0.0294

Table 19: China [Hong Kong] Magic Formula Results After Transaction Costs

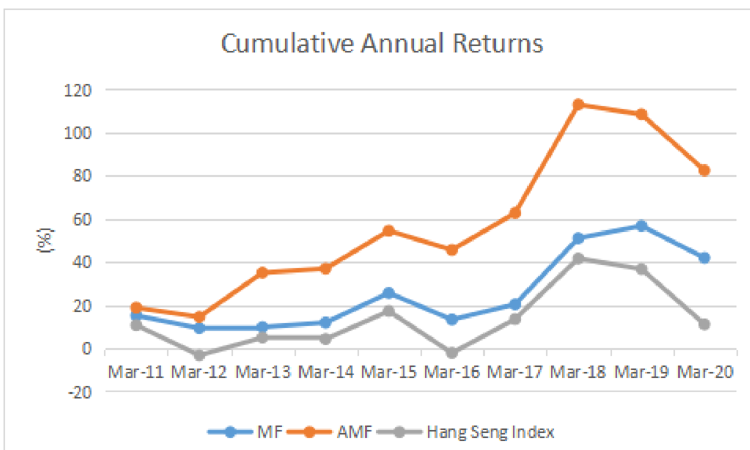

Fig. 5. China [Hong Kong] Cumulative Annual Returns After Transaction Costs

Returns against the Hang Seng index of Hong Kong - as our proxy for China - were 4 times greater for our MF portfolio, and 8 times greater for our AMF portfolio versus simply holding the index itself. Volatility is lower for both constructed portfolios.

7.5 South Africa

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	42.72%	32.45%	33.84%	23.95%	6.71%	-0.55%	3.15%	21.32%	-14.59%	-13.48%
AMF	33.75%	32.20%	28.00%	22.12%	10.85%	4.81%	2.34%	20.43%	-3.63%	-14.44%
FTSE/JSE 40	12.40%	1.95%	19.10%	21.94%	7.02%	0.27%	-2.11%	8.03%	3.03%	-18.97%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	207.74%	11.90%	20.18%	0.3787
AMF	226.32%	12.55%	16.24%	0.5111
FTSE/JSE 40	57.70%	4.66%	11.61%	0.0348

Table 20: South Africa Magic Formula Results Before Transaction Costs

Portfolio	'10	'11	'12	'13	'14	'15	'16	'17	'18	'19
MF	36.65%	27.48%	28.72%	19.89%	4.50%	-2.20%	1.32%	17.55%	-16.12%	-15.02%
AMF	28.63%	27.25%	23.51%	18.26%	8.20%	2.81%	0.61%	16.75%	-5.25%	-15.97%
FTSE/JSE 40	12.40%	1.95%	19.10%	21.94%	7.02%	0.27%	-2.11%	8.03%	3.03%	-18.97%

Portfolio	Total Returns	CAGR	STD	Sharpe Ratio
MF	133.26%	8.84%	18.51%	0.2476
AMF	148.71%	9.54%	14.87%	0.3554
FTSE/JSE 40	57.70%	4.66%	11.61%	0.0348

Table 21: South Africa Magic Formula Results After Transaction Costs

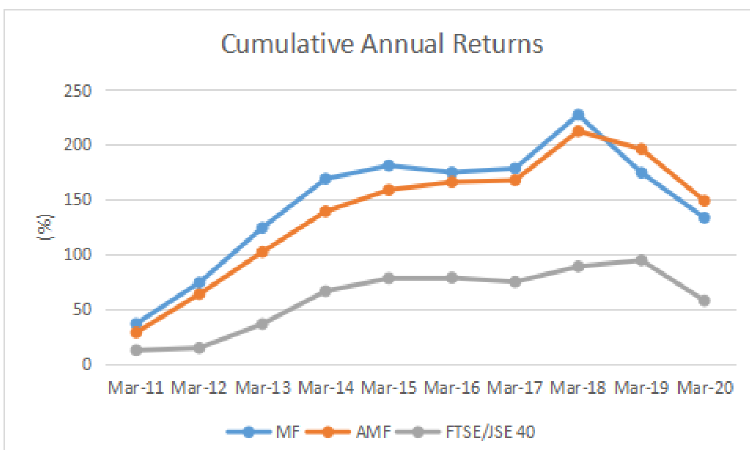

Fig. 6. South Africa Cumulative Annual Returns After Transaction Costs

Finally, both of our constructed portfolios outperform the FTSE/JSE index by about 2.5 times on a total returns basis, however, volatility is higher in both cases, as is the Sharpe ratio - by at least an order of magnitude.

As stated earlier - the spreadsheets containing the workings for all of the above are available in the following GitHub repository: `https://github.com/ng0021an/magic`.

8 Statistical Analysis

The Sharpe ratio can be thought of as a test statistic of a single-sample *t*-test for portfolio returns against the risk-free rate of returns, indicating the statistical significance of the hypothesis that the constructed portfolio's returns is higher than the risk-free rate. Expanding on this approach, we can perform pair-wise two-sample *t*-tests between the MF portfolio, AMF portfolio and underlying market indices, in order to draw statistical conclusions about the relative performance between the three. The *p*-values of the tests are given below:

Market	MF to Market	AMF to Market	AMF to MF
Brazil	0.1053	0.0979	0.5005
Russia	0.0099	0.0166	0.4715
India	0.3083	0.2371	0.4105
China [HK]	0.3265	0.1964	0.3061
South Africa	0.1376	0.1006	0.4956

Table 22: Consolidated *t*-test *p*-values Between Portfolios

For all markets under consideration, we cannot conclude at a 30% significance level that the AMF portfolio outperforms the MF portfolio, even though the difference between total returns are stark for some markets like China and India. More interestingly, despite these eyewatering differences in total returns, for these two countries we cannot conclude that either a) the MF portfolios outperform the market indices at a 30% significance level, or b) the AMF porfolios outperform the market indices at a 15% significance level. There is an observable improvement in the test statistics for the MF versus AMF portfolios, but this is insufficient to bring the *p*-value into an acceptable range.

For Russia, the statistics allow us to conclude at the 1% significance level that the MF portfolio outperforms the market, and similarly we can conclude at the 2% significance level that the AMF portfolio outperform the market. Despite a small out-performance in total returns when compared to the MF portfolio, the AMF portfolio did not strengthen overall performance, and actually produced a lower *p*-value compared to the MF portfolio.

The *p*-values for Brazil stay at an acceptable significance level of 10%, whilst the *p*-values for South Africa stay within the 15% significance level, which lay on the border of the acceptable range. Overall, our analysis suggests that we can be very confident with the MF and AMF portfolios for Russia, but less so with the constructed portfolios for Brazil and South Africa. For India and China, the statistics do not suggest a significant difference between our constructed portfolios and the markets, and the observed outperformance could be a result of pure chance. Due to the small number of samples we are using (10 data points for 10 years), there is a possibility of bias in the produced statistics which might be improved by running the experiment for a longer period. As a result, these statistics may act more as a reference point than an absolute investment philosophy.

Another approach to measure portfolio performance is the one taken by CAPM model, which can be generalised as a linear regression of the portfolio in interest against the market index, where the coefficient for the independent variable (the market index) represents the beta or the exposure to the market index and the intercept represents the alpha or the excess returns intrinsic to the portfolio's construction. The detailed results of Ordinary Least Square Regression for both the MF and AMF portfolios against the market indices are presented in Appendix B.

The intercept is positive for all of the markets for both MF and AMF indicating the presence of excess alpha, while beta is within the range of 0.7 to 1.25, implying that the these portfolios are highly correlated with the markets. The t-statistics show that the beta is significant for all of the markets while alpha may not be statistically significant for India and South Africa. A high correlation with market index is expected as stocks are selected from the components of the market index itself. A positive alpha asserts the excess value of the selection method. However even with a positive alpha, a beta value that is greater than one may still cause the portfolio values to fall below that of the market indices, which can be observed in some years.

9 Conclusion

This capstone project examined and bac tested Joel Greenblatt's Magic Formula investment strategy [1] in the equity markets of the BRICS countries (Brazil, Russia, India, China and South Africa) over a ten year period from 2010 to 2019. Greenblatt's Magic Formula uses the return on capital (ROC) and earnings yield (EBIT/EV) ratios as factors to rank stocks and form a potential market-beating portfolio. This project applied the Magic Formula on the components of the stock market indices rather than the entire universe of stocks from each country. The project sought to determine whether such an application of the MF investment strategy can be used successfully in emerging markets, the BRICS in particular, to outperform their respective stock market benchmark indices. In addition, the project proposed an augmented Magic Formula which uses the percentage change in earnings per share using EBIT as a third factor in the formation of the portfolio.

The results of the study indicate that both the MF and augmented MF portfolios outperformed their respective benchmark indices in all nations over the ten year study period, as shown by the compounded annual returns (factoring in transaction costs) in the following table:

Portfolio	Brazil	Russia	India	China [HK]	South Africa
MF	7.98%	16.36%	6.08%	3.57%	8.84%
AMF	8.21%	16.42%	7.60%	6.20%	9.54%
Benchmark Index	1.85%	5.63%	5.06%	1.06%	4.66%

Table 23: BRICS MF and AMF CAGR vs Benchmarks

Moreover, both the MF and augmented MF portfolios have higher Sharpe ratios than the benchmark indices in all cases, indicating higher risk-adjusted returns. The outperformance of the MF and AMF portfolios against the benchmark indices across all the BRICS nations appears remarkable, but is similar to the significant outperformance that Greenblatt measured for the MF portfolios in the US stock market (30.8% vs. 12.4%). As such, we can state that the Magic Formula investment strategy remains a strategy worthy of consideration for selecting a small subset of an index (say the top quartile ranking) with a good probability of beating the index on an absolute and risk-adjusted basis over a long time period.

Our novel contribution to the research - the modification of the Magic Formula portfolio by factoring in the percentage change in earnings per share as a third factor - outperformed the original MF portfolio over the ten year study period in all the BRICS nations. This indicates that the percentage change in earnings per share can potentially be used as an added filter to further improve the returns of the Magic Formula investment strategy.

References

[1] Greenblatt, J., 2005. "The Little Book That Beats the Market". Wiley.

[2] Martin, R. A., 2020. "A Critical Look At Greenblatt's Magic Formula".

[3] O'Shaughnessy, J., 2011. "What Works on Wall Street: The Classic Guide to the Best-Performing Investment Strategies of All Time".

[4] Flavelle, L., 2018. "Has The Magic Formula Lost Its Sparkle?".

[5] Piotroski, J. D., 2002. ""Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers".

[6] Blackburn, D. W., and Cakici, N., 2017. "The Magic Formula: Value, Profitability, and the Cross Section of Global Stock Returns".

[7] Persson, V., and Selander, N., 2009. "Backtesting "The Magic Formula" In The Nordic Region".

[8] Davydov, D., Tikkanen, J., and Aijo, J., 2016. "Magic Formula vs. Traditional Value Investment Strategies in the Finnish Stock Market".

[9] Sjobeck, E., and Verngren, J., 2019. "Magic Formula Has Its Magic And Momentum Has Its Moments - A Study On Magic Formula And Momentum On The Swedish Stock Market".

[10] Fama, E. F., and French, K. R., 1992. "The Cross-Section of Expected Stock Returns". *The Journal of Finance,* **47**(2), pp. 427–465.

[11] Fama, E. F., and French, K. R., 1993. "Common Risk Factors in the Returns On Stocks And Bonds". *Journal of Financial Economics,* **33**, pp. 3–56.

[12] Fu, S., and Xia, C., 2016. "Does Magic Formula Investing Work In Hong Kong Stock Market?".

[13] Fama, E. F., and MacBeth, J. D., 1973. "Risk, Return and Equilibrium: Empirical Tests". *Journal Of Political Economy,* **81**(3), pp. 607–636.

[14] Postma, P. P. M., 2015. "Magic Formula Investing In The Benelux".

[15] Madha, A., 2020. "Joel Greenblatt's Magic Formula In The Indian Context - Does It Work?".

[16] Ker-Fox, J. G., 2017. "Magic Formula Optimisation In The South African Market".

[17] Luo, M., 2019. "Case Study of Magic Formula Based on Value Investment in Chinese A-shares Market". In Advances in Computational Science and Computing, Springer International Publishing, pp. 177–194.

[18] de Paula, A. G. J., 2016. "Backtesting the Magic Formula in the Brazilian Stock Market".

[19] Mustafin, A., 2018. "Analysis of the Value Investing Strategy "Magic Formula"".

[20] Reed, P., 2016. "Historical Index Constituents in Bloomberg".

[21] Chan, G., 2020. "TIKR: A Lightweight, Cost-Effective Financial Data Terminal".

[22] Yahoo! Finance. `https://uk.finance.yahoo.com/`. Accessed: 2021-01-14.

[23] Sharpe, W. F., 1994. "The Sharpe Ratio". *The Journal of Portfolio Management,* **21**(1), pp. 49–58.

[24] Bond Historical Data. `http://www.worldgovernmentbonds.com/bond-historical-data/`. Accessed: 2021-01-14.

[25] Markov, V., 2019. Bayesian trading cost analysis and ranking of broker algorithms.

Appendices

A Python TIKR API Scraper

Below is the bulk of the code for the Python API scraper used to retrieve financial data and calculate ROC/yield/EPS values for various companies. Note that this appendix is a rough guideline only - some components have been partially cut down to save on space, whilst illustrating the core concept. In order to execute this code in it's entirety, please refer to the GitHub repository `https://github.com/ng0021an/magic`.

```
import requests,math
from datetime import datetime

import pandas as pd
from collections import OrderedDict

KEY_MAP = {21: "operating_income", 1004: "fixed_asset", 1008: "current_asset",
           1096: "cash", 1009: "current_liability", 1046: "short_term_borrow",
           1297: "current_long_term_debt", 342: "diluted_share_outstanding",
           1049: "long_term_debt"}
DATE_TIME_FORMAT = '%Y-%m-%dT%H:%M:%S.%fZ'

#REPLACE THIS WITH YOUR AUTH KEY RETRIEVED BY INSPECTING THE REQUEST IN CHROME
AUTH = "eyJraWQiOiI4SXJoQ244VlZ...f3hL4lCKW2dL0Q"

cid: 881725
p: "1"
repid: 1
v: "v0"
pd.read_excel('TIKR_Symbols.xls', index_col=0)

def search(sy):
    url = "https://tjpay1dyt8-dsn.algolia.net..."
    post_dat = f"{{\"params\":\"query={sy}&distinct=2\"}}"
    x = requests.post(url, data = post_dat,
        headers = {"Content-Type":"application/x-www-form-urlencoded"})
    return x.json()

def find_stock(search_res, ex):
    for record in search_res['hits']:
        if record['exchangesymbol'] == ex:
            return record
    return None

def load_price(cid, tid):
    url = "https://rwrjol17eb.execute-api.us-east-1.amazonaws.com/prod/price"
    post_dat = f"{{\"auth\":\"{AUTH}\",\"tid\":{tid}, ... ,\"v\":\"v0\"}}"
    x = requests.post(url, data = post_dat,
        headers = {"Content-Type":"application/json;charset=UTF-8"})
    return x.json()

def load_finance(cid):
    url = "https://rwrjol17eb.execute-api.us-east-1.amazonaws.com/prod/fin"
    post_dat = f"{{\"auth\":\"{AUTH}\",...,\"v\":\"v0\"}}"
    x = requests.post(url, data = post_dat,
        headers = {"Content-Type":"application/json;charset=UTF-8"})
    return x.json()
```

```
def populate_fin_rec(fin_map, rec):
    if not rec['financialperiodid'] in fin_map:
        fin_map[rec['financialperiodid']] = {KEY_MAP[key]:0 for key in KEY_MAP}
    if rec['dataitemid'] in KEY_MAP:
        fin_map[rec['financialperiodid']][KEY_MAP[rec['dataitemid']]]
            = float(rec['dataitemvalue'])

def get_date_fin_price(cid,tid):
    raw_dat = load_finance(cid)
    fin_map = {}
    for rec in raw_dat['data']:
        populate_fin_rec(fin_map, rec)
    dates = raw_dat['dates']
    merge_fin_map_into_date(fin_map, dates)
    price = load_price(cid, tid)['price']
    merge_price_into_date(price, dates)
    return dates

def build_key(rec):
    return (rec['calendaryear'], rec['calendarquarter'])

def get_date(date_str):
    return datetime.strptime(date_str, '%Y-%m-%dT%H:%M:%S.%fZ').date()

def merge_fin_map_into_date(fin_map, dates):
    for rec in dates:
        for key in fin_map[rec['financialperiodid']]:
            rec[key] = fin_map[rec['financialperiodid']][key]

def merge_price_into_date(price, dates):
    i = j = 0
    dates[j]['priceclose'] = math.nan
    while (i < len(price)) and (j < len(dates)):
        key_price = get_date(price[i]['d'])
        key_dates = get_date(dates[j]['fiperiodenddate'])
        if key_price <= key_dates:
            if (key_price.year == key_dates.year)
                and (key_price.month == key_dates.month):
                dates[j]['priceclose'] = float(price[i]['c'])
            i += 1
        else:
            if math.isnan(dates[j]['priceclose']):
                if key_dates.year > 2009:
                    print(f"Critial ERROR!!! price not found for date {key_dates}")
            j += 1
            if j < len(dates):
                dates[j]['priceclose'] = math.nan


def retrieve(symbol_data):
    cid = symbol_data['companyid']
    tid = symbol_data['tradingitemid']
    date_fin_price = get_date_fin_price(cid,tid)

    return date_fin_price
```

```
def lookup(sy, ex):
    search_res = search(sy)
    sym_dat = find_stock(search_res, ex)
    if not sym_dat:
        print(f"CRITICAL ERROR!!! No search result for {sy} {ex}")
        return None
    dat_arr = retrieve(sym_dat)
    prev_rec = None
    for rec in dat_arr:
        if not prev_rec:
            rec['eps'] = math.nan
        elif rec['diluted_share_outstanding'] * prev_rec['operating_income'] == 0:
            rec['eps'] = math.nan
            print(f"WARNING: ...")
        else:
            rec['eps'] = ...

        invested_cap = ...
        enterprise_val = ...
        if invested_cap == 0:
            rec['roic'] = math.nan
            print(f"WARNING: invested_cap is 0: {build_key(rec)}")
        else:
            rec['roic'] = rec['operating_income']/invested_cap

        if enterprise_val == 0:
            rec['earning_yield'] = math.nan
            print(f"WARNING: enterprise_val is 0: {build_key(rec)}")
        else:
            rec['earning_yield'] = rec['operating_income']/enterprise_val


        prev_rec = rec

    return dat_arr

file_name = 'TIKR_Symbols.xls'
current_year = 2020

def get_all_sy(sy_pd):
    all_sy = set()
    for year in sy_pd.columns:
        all_sy.update(sy_pd[year].dropna())
    return all_sy

def add_to_data_by_years(data_by_years, sy, all_data_sy):
    for rec in all_data_sy:
        (year, quarter) = build_key(rec)
        if (year in data_by_years) and (sy in data_by_years[year].index):
            cur_quarter = data_by_years[year]['calendarquarter'][sy]
            if math.isnan(cur_quarter) or cur_quarter < quarter:
                for field in data_by_years[year].columns:
                    data_by_years[year][field][sy] = rec[field]
```

```
def get_data_for_market(market, exchange):
    print(f"=======GET DATA FOR MARKET {market} EXCHANGE {exchange} ========")
    sy_pd = pd.read_excel(file_name, sheet_name=market, dtype=str)
    all_sy = get_all_sy(sy_pd)
    data_by_years = OrderedDict()
    for year in sy_pd.keys():
        data_by_years[year] =
            pd.DataFrame(columns = ['roic', 'earning_yield', 'eps', 'priceclose',
                'calendarquarter'], index = sy_pd[year].dropna())
    for sy in all_sy:
        print(sy)
        all_data_sy = lookup(sy, exchange)
        if all_data_sy:
            add_to_data_by_years(data_by_years, sy, all_data_sy)

    return data_by_years

pd.set_option('display.max_rows', None)
```

B OLS Regressions: Constructed Portfolios vs Market Indices

B.1 Brazil

B.1.1 Brazil MF Portfolio Statistics

```
==============================================================================
Dep. Variable:                     MF   R-squared:                       0.557
Model:                            OLS   Adj. R-squared:                  0.502
Method:                 Least Squares   F-statistic:                     10.06
Date:                Sun, 17 Jan 2021   Prob (F-statistic):             0.0132
Time:                        12:16:58   Log-Likelihood:                -37.634
No. Observations:                  10   AIC:                             79.27
Df Residuals:                       8   BIC:                             79.87
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         10.5261      3.754      2.804      0.023       1.869      19.183
MKT            0.7303      0.230      3.172      0.013       0.199       1.261
==============================================================================
Omnibus:                        0.015   Durbin-Watson:                   1.790
Prob(Omnibus):                  0.992   Jarque-Bera (JB):                0.231
Skew:                           0.050   Prob(JB):                        0.891
Kurtosis:                       2.263   Cond. No.                         16.6
==============================================================================
```

B.1.2 Brazil AMF Portfolio Statistics

```
==============================================================================
Dep. Variable:                    AMF   R-squared:                       0.563
Model:                            OLS   Adj. R-squared:                  0.508
Method:                 Least Squares   F-statistic:                     10.30
Date:                Sun, 17 Jan 2021   Prob (F-statistic):             0.0124
Time:                        17:40:26   Log-Likelihood:                -36.817
No. Observations:                  10   AIC:                             77.63
Df Residuals:                       8   BIC:                             78.24
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         10.6680      3.460      3.083      0.015       2.690      18.646
MKT            0.6809      0.212      3.210      0.012       0.192       1.170
==============================================================================
Omnibus:                        0.260   Durbin-Watson:                   1.510
Prob(Omnibus):                  0.878   Jarque-Bera (JB):                0.304
Skew:                           0.283   Prob(JB):                        0.859
Kurtosis:                       2.361   Cond. No.                         16.6
==============================================================================
```

B.2 Russia

B.2.1 Russia MF Portfolio Statistics

```
==============================================================================
Dep. Variable:                     MF   R-squared:                       0.414
Model:                            OLS   Adj. R-squared:                  0.341
Method:                 Least Squares   F-statistic:                     5.657
Date:                Sun, 17 Jan 2021   Prob (F-statistic):             0.0447
Time:                        12:16:58   Log-Likelihood:                -40.034
No. Observations:                  10   AIC:                             84.07
Df Residuals:                       8   BIC:                             84.67
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         18.4705      5.295      3.488      0.008       6.261      30.680
MKT            0.9239      0.388      2.378      0.045       0.028       1.820
==============================================================================
Omnibus:                        3.083   Durbin-Watson:                   1.284
Prob(Omnibus):                  0.214   Jarque-Bera (JB):                0.902
Skew:                           0.712   Prob(JB):                        0.637
Kurtosis:                       3.365   Cond. No.                         15.4
==============================================================================
```

B.2.2 Russia AMF Portfolio Statistics

```
==============================================================================
Dep. Variable:                    AMF   R-squared:                       0.508
Model:                            OLS   Adj. R-squared:                  0.447
Method:                 Least Squares   F-statistic:                     8.276
Date:                Sun, 17 Jan 2021   Prob (F-statistic):             0.0206
Time:                        17:40:26   Log-Likelihood:                -41.105
No. Observations:                  10   AIC:                             86.21
Df Residuals:                       8   BIC:                             86.82
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         17.0998      5.893      2.902      0.020       3.510      30.689
MKT            1.2438      0.432      2.877      0.021       0.247       2.241
==============================================================================
Omnibus:                        1.284   Durbin-Watson:                   0.881
Prob(Omnibus):                  0.526   Jarque-Bera (JB):                0.640
Skew:                           0.592   Prob(JB):                        0.726
Kurtosis:                       2.632   Cond. No.                         15.4
==============================================================================
```

B.3 India

B.3.1 India MF Portfolio Statistics

```
==============================================================================
Dep. Variable:                     MF   R-squared:                       0.815
Model:                            OLS   Adj. R-squared:                  0.792
Method:                 Least Squares   F-statistic:                     35.31
Date:                Sun, 17 Jan 2021   Prob (F-statistic):           0.000345
Time:                        12:16:58   Log-Likelihood:                -34.633
No. Observations:                  10   AIC:                             73.27
Df Residuals:                       8   BIC:                             73.87
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.6109      2.952      1.223      0.256      -3.197      10.419
MKT            1.0629      0.179      5.942      0.000       0.650       1.475
==============================================================================
Omnibus:                        0.236   Durbin-Watson:                   1.963
Prob(Omnibus):                  0.889   Jarque-Bera (JB):                0.397
Skew:                          -0.128   Prob(JB):                        0.820
Kurtosis:                       2.058   Cond. No.                         17.9
==============================================================================
```

B.3.2 India AMF Portfolio Statistics

```
==============================================================================
Dep. Variable:                    AMF   R-squared:                       0.854
Model:                            OLS   Adj. R-squared:                  0.836
Method:                 Least Squares   F-statistic:                     46.77
Date:                Sun, 17 Jan 2021   Prob (F-statistic):           0.000132
Time:                        17:40:26   Log-Likelihood:                -34.277
No. Observations:                  10   AIC:                             72.55
Df Residuals:                       8   BIC:                             73.16
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          4.9037      2.849      1.721      0.124      -1.666      11.473
MKT            1.1805      0.173      6.839      0.000       0.782       1.578
==============================================================================
Omnibus:                        3.449   Durbin-Watson:                   1.892
Prob(Omnibus):                  0.178   Jarque-Bera (JB):                1.436
Skew:                          -0.928   Prob(JB):                        0.488
Kurtosis:                       3.053   Cond. No.                         17.9
==============================================================================
```

B.4 China [Hong Kong]

B.4.1 China [Hong Kong] MF Portfolio Statistics

```
==============================================================================
Dep. Variable:                     MF   R-squared:                       0.827
Model:                            OLS   Adj. R-squared:                  0.805
Method:                 Least Squares   F-statistic:                     38.22
Date:                Sun, 17 Jan 2021   Prob (F-statistic):           0.000264
Time:                        12:16:58   Log-Likelihood:                -29.082
No. Observations:                  10   AIC:                             62.16
Df Residuals:                       8   BIC:                             62.77
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.3194      1.584      2.095      0.069      -0.334       6.972
MKT            0.6903      0.112      6.182      0.000       0.433       0.948
==============================================================================
Omnibus:                        1.445   Durbin-Watson:                   2.002
Prob(Omnibus):                  0.485   Jarque-Bera (JB):                0.905
Skew:                          -0.678   Prob(JB):                        0.636
Kurtosis:                       2.421   Cond. No.                         14.3
==============================================================================
```

B.4.2 China [Hong Kong] AMF Portfolio Statistics

```
==============================================================================
Dep. Variable:                    AMF   R-squared:                       0.893
Model:                            OLS   Adj. R-squared:                  0.880
Method:                 Least Squares   F-statistic:                     66.72
Date:                Sun, 17 Jan 2021   Prob (F-statistic):           3.76e-05
Time:                        17:40:26   Log-Likelihood:                -28.591
No. Observations:                  10   AIC:                             61.18
Df Residuals:                       8   BIC:                             61.79
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          5.8333      1.508      3.868      0.005       2.355       9.311
MKT            0.8683      0.106      8.168      0.000       0.623       1.113
==============================================================================
Omnibus:                        1.816   Durbin-Watson:                   2.627
Prob(Omnibus):                  0.403   Jarque-Bera (JB):                0.861
Skew:                          -0.252   Prob(JB):                        0.650
Kurtosis:                       1.654   Cond. No.                         14.3
==============================================================================
```

B.5 South Africa

B.5.1 South Africa MF Portfolio Statistics

```
==============================================================================
Dep. Variable:                     MF   R-squared:                       0.489
Model:                            OLS   Adj. R-squared:                  0.425
Method:                 Least Squares   F-statistic:                     7.643
Date:                Sun, 17 Jan 2021   Prob (F-statistic):             0.0245
Time:                        12:16:58   Log-Likelihood:                -40.356
No. Observations:                  10   AIC:                             84.71
Df Residuals:                       8   BIC:                             85.32
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          7.1561      5.365      1.334      0.219      -5.214      19.527
MKT            1.2146      0.439      2.765      0.024       0.201       2.228
==============================================================================
Omnibus:                        0.122   Durbin-Watson:                   1.230
Prob(Omnibus):                  0.941   Jarque-Bera (JB):                0.101
Skew:                           0.085   Prob(JB):                        0.951
Kurtosis:                       2.538   Cond. No.                         13.6
==============================================================================
```

B.5.2 South Africa AMF Portfolio Statistics

```
==============================================================================
Dep. Variable:                    AMF   R-squared:                       0.571
Model:                            OLS   Adj. R-squared:                  0.517
Method:                 Least Squares   F-statistic:                     10.65
Date:                Sun, 17 Jan 2021   Prob (F-statistic):             0.0115
Time:                        17:40:26   Log-Likelihood:                -37.305
No. Observations:                  10   AIC:                             78.61
Df Residuals:                       8   BIC:                             79.22
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          8.0789      3.954      2.043      0.075      -1.039      17.197
MKT            1.0566      0.324      3.263      0.011       0.310       1.803
==============================================================================
Omnibus:                        2.993   Durbin-Watson:                   1.228
Prob(Omnibus):                  0.224   Jarque-Bera (JB):                1.143
Skew:                           0.827   Prob(JB):                        0.565
Kurtosis:                       3.079   Cond. No.                         13.6
==============================================================================
```