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Quant GEM

Quantitative investing in Global Emerging Markets (GEM)

What's so unique about GEM?
The GEM universe comprises 21 diverse countries with differing market microstructures, market access, limitations on shorting, and trading liquidity. This report provides a thorough overview of various GEM markets as well as the challenges and limitations investors will face when implementing an investment strategy in these markets.

GEM Alpha versus Beta
We separate GEM alpha from Beta and find that alpha opportunity and performance is still auspicious despite significant levels of GEM market volatility and current Beta driven underperformance.

Bridging the gap between backtesting and the real world
We consider a variety of different real-world constraints that are unique to GEM and develop a realistic transaction cost model for trading GEM equities. We also show that capacity issues for large AUM can be alleviated by taking advantage of stocks listed on multiple exchanges.

Robust Multi-Factor model — a dynamic factor weighting algorithm
We explore a wide range of factor weighting schemes to build our GEM alpha. Our final Robust Multi-Factor (RMF) model is based on an alpha risk parity technique, which has low turnover, high capacity and strong performance.

Profitable investable strategies in emerging markets
Last, we develop a series of real-world investable strategies including alternative beta, active enhanced indexing and absolute return portfolios.

Source: gettyimages.com

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A letter to our readers

Emerging markets — opportunities and challenges

The recent sell-off of global emerging market stocks (GEM) has raised serious concerns for this important asset class. However, for systematic investors, GEM is an appealing investment universe full of potential opportunities. Not only is it easier to harvest alpha, but GEM beta also provides great diversification benefit to an overall asset allocation strategy. There are also significant challenges when investing in GEM such as market access restrictions, taxation, limits on shorting, and trading liquidity. As such, GEM investment strategies can be very different from how we traditionally invest in developed markets (DM).

Realistic constraints and transaction cost model

For long/short quant investors, GEM posses a potential challenge due to the various shorting constraints within each market. An alternative investment approach is to invest in a long only portfolio and short the GEM market index. But the performance tends to be much lower, as we can't fully capture the alpha opportunities on the short side. In addition, capacity is a much bigger issue in GEM than DM, as liquidity tends to be lower. We show how investing in the same company listed in multiple exchanges[1] can help improve liquidity and increase capacity. We also introduce a realistic market impact model to better account for transaction costs.

A better quant multi-factor model using dynamic weighting algorithms

Quant factors generally produce better performance in GEM than in DM. Factors in GEM also show interesting regional patterns. We discuss various approaches of adjusting and neutralizing regional differences at the signal level. We compare a variety of factor weighting algorithms, and find alpha risk parity weighting has low turnover, high capacity, and attractive risk adjusted performance. We build our Robust Multi-Factor (RMF) model based on this dynamic weighting scheme for some common style factors[2].

Investable strategies in emerging markets

We discuss several profitable strategies in GEM. All the strategies are based on realistic constraints and transaction cost assumptions. We find that low risk investing in GEM via minimum variance (MinVar) has low turnover, high capacity, and outperforms the market significantly, with a Sharpe ratio of 1.2x. We also introduce an active strategy without referencing to any specific benchmarks. Lastly, we demonstrate a series of enhanced indexing strategies tracking the MSCI EM index with two different alpha models — the RFM introduced in this research and our N-LASR global stock selection model — both models have delivered Sharpe ratios around 1.4x.

Regards,

Yin, Miguel, Javed, John, and Sheng
Deutsche Bank Quantitative Strategy

[1] For example ADRs, GDRs, and cross listings.

[2] These factors are region and sector normalized, based on similar algorithm as in Wang, et al [2013].

GEM screens

Stock screens based on the Robust Multi-Factor (RMF) model

Figure 1 and Figure 2 list the best 40 long and short ideas for the MSCI EM universe, based on our Robust Multi-Factor (RMF) model. A full list of all MSCI EM stocks is available upon request.

Figure 1: Best long ideas based on the Robust Multi-Factor (RMF) model for MSCI EM universe

Ticker	Company Name	Country	GICS Sector	RMF Score (more positive = more likely to outperform)
017670 KS	SK TELECOM CO	South Korea	Telecommunication Services	2.97
003600 KS	SK HOLDINGS	South Korea	Industrials	2.94
2542 TT	HIGHWEALTH CONSTRUCTION	Taiwan	Financials	2.66
902 HK	HUANENG POWER INTL H(HKD	China	Utilities	2.59
000270 KS	KIA MOTORS CORP	South Korea	Consumer Discretionary	2.52
CAIR IB	CAIRN INDIA	India	Energy	2.48
CAP CC	CAP	Chile	Materials	2.24
ECOPETL CB	ECOPETROL	Colombia	Energy	2.13
ENTEL CC	ENTEL	Chile	Telecommunication Services	2.11
OINL IB	OIL INDIA	India	Energy	2.10
1398 HK	ICBC H	China	Financials	2.09
KIO SJ	KUMBA IRON ORE	South Africa	Materials	2.07
ROSNS RU	ROSNEFT (RUB)	Russia	Energy	2.03
005930 KS	SAMSUNG ELECTRONICS CO	South Korea	Information Technology	2.00
005380 KS	HYUNDAI MOTOR CO	South Korea	Consumer Discretionary	1.86
ETEL EY	TELECOM EGYPT	Egypt	Telecommunication Services	1.79
3968 HK	CHINA MERCHANTS BANK H	China	Financials	1.78
2362 TT	CLEVO COMPANY	Taiwan	Information Technology	1.77
2474 TT	CATCHER TECH CO	Taiwan	Information Technology	1.77
CPLE6 BS	COPEL PNB	Brazil	Utilities	1.77
NA	MEGAFON GDR	Russia	Telecommunication Services	1.74
3988 HK	BANK OF CHINA H	China	Financials	1.73
CMIG4 BS	CEMIG PN	Brazil	Utilities	1.72
TRNFP RX	TRANSNEFT PREF (RUB)	Russia	Energy	1.70
030200 KS	KT CORP	South Korea	Telecommunication Services	1.68
939 HK	CHINA CONSTRUCTION BK H	China	Financials	1.67
3900 HK	GREENTOWN CHINA HLDGS	China	Financials	1.66
SOL SJ	SASOL	South Africa	Energy	1.64
096770 KS	SK INNOVATION CO	South Korea	Energy	1.64
COPEC CC	EMPRESAS COPEC	Chile	Energy	1.63
VOD SJ	VODACOM GROUP	South Africa	Telecommunication Services	1.63
CORPBANC CC	CORPBANCA	Chile	Financials	1.62
PWGR IB	POWER GRID CORP OF INDIA	India	Utilities	1.62
386 HK	CHINA PETRO & CHEM H	China	Energy	1.61
PTTGC TB	PTT GLOBAL CHEMICAL	Thailand	Materials	1.59
PTTEP TB	PTT EXPLORATION & PROD	Thailand	Energy	1.59
PFBCOLO CB	BANCOLOMBIA PREF	Colombia	Financials	1.58
TPE PW	TAURON POLSKA ENERGIA	Poland	Utilities	1.54
119 HK	POLY PROPERTY GROUP CO	China	Financials	1.54
836 HK	CHINA RESOURCES POWER	China	Utilities	1.53

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 2: Best short ideas based on the Robust Multi-Factor (RMF) model for MSCI EM universe

Ticker	Company Name	Country	GICS Sector	RMF Score (more negative = more likely to underperform)
MPXE3 BS	ENEVA	Brazil	Utilities	-3.82
006360 KS	GS ENGINEERING & CONSTR.	South Korea	Industrials	-3.37
2609 TT	YANG MING MARINE TRANSP	Taiwan	Industrials	-3.27
2353 TT	ACER	Taiwan	Information Technology	-3.26
011200 KS	HYUNDAI MERCHANT MARINE	South Korea	Industrials	-2.92
2866 HK	CHINA SHIPPING CONTAIN H	China	Industrials	-2.83
SIEM IB	SIEMENS INDIA	India	Industrials	-2.82
ANG SJ	ANGLOGOLD ASHANTI	South Africa	Materials	-2.81
2498 TT	HTC CORP	Taiwan	Information Technology	-2.77
2603 TT	EVERGREEN MARINE CORP	Taiwan	Industrials	-2.73
2600 HK	ALUMINUM CORP OF CHINA H	China	Materials	-2.68
3800 HK	GCL POLY ENERGY	China	Information Technology	-2.66
1314 TT	CHINA PETROCHEMICAL DEV	Taiwan	Materials	-2.65
1919 HK	CHINA COSCO HOLDINGS H	China	Industrials	-2.53
IHH MK	IHH HEALTHCARE	Malaysia	Health Care	-2.47
1211 HK	BYD CO H	China	Consumer Discretionary	-2.44
TRUE TB	TRUE CORP	Thailand	Telecommunication Services	-2.43
1171 HK	YANZHOU COAL MINING CO H	China	Energy	-2.31
1066 HK	SHANDONG WEIGAO GP MED H	China	Health Care	-2.31
010620 KS	HYUNDAI MIPO DOCKYARD	South Korea	Industrials	-2.28
BUMI IJ	BUMI RESOURCES	Indonesia	Energy	-2.24
GENP MK	GENTING PLANTATIONS	Malaysia	Consumer Staples	-2.22
LAN CC	LATAM AIRLINES GROUP	Chile	Industrials	-2.13
RADL3 BS	RAIADROGASIL	Brazil	Consumer Staples	-2.09
001740 KS	SK NETWORKS	South Korea	Industrials	-2.05
TMGH EY	TMG HOLDING	Egypt	Financials	-2.04
RBXY IB	RANBAXY LABORATORIES	India	Health Care	-2.04
042670 KS	DOOSAN INFRACORE CO	South Korea	Industrials	-2.04
AMS SJ	ANGLO AMERICAN PLATINUM	South Africa	Materials	-2.01
CEMEXCPO MM	CEMEX CPO	Mexico	Materials	-2.00
763 HK	ZTE CORP H	China	Information Technology	-1.98
HAR SJ	HARMONY GOLD MINING CO	South Africa	Materials	-1.95
CLH CB	CEMEX LATAM HOLDINGS	Colombia	Materials	-1.94
CHMF RX	SEVERSTAL (RUB)	Russia	Materials	-1.89
URKA RX	URALKALI COMMON (RUB)	Russia	Materials	-1.89
012630 KS	HYUNDAI DEVELOPMENT CO	South Korea	Industrials	-1.85
MMC MK	MALAYSIA MINING CORP	Malaysia	Industrials	-1.83
QUAL3 BS	QUALICORP	Brazil	Health Care	-1.81
UBBL IS	UNITED BREWERIES	India	Consumer Staples	-1.78
003490 KS	KOREAN AIR CO	South Korea	Industrials	-1.78

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Stock screens based on the N-LASR machine learning model

Figure 3 and Figure 4 list the best 40 long and short ideas for the MSCI EM universe based on our N-LASR machine learning model (see details in Wang, *et al* [2012, 2013]). A full list of the MSCI EM stocks is available upon request.

Figure 3: Best long ideas based on the machine learning model (N-LASR model) for MSCI EM universe

Ticker	Company Name	Country	GICS Sector	N-LASR Score (more positive = more likely to outperform)
3968 HK	CHINA MERCHANTS BANK H	China	Financials	2.90
003600 KS	SK HOLDINGS	South Korea	Industrials	2.84
119 HK	POLY PROPERTY GROUP CO	China	Financials	2.66
PFBCOLO CB	BANCOLOMBIA PREF	Colombia	Financials	2.57
LBH SJ	LIBERTY HOLDINGS	South Africa	Financials	2.52
2888 TT	SHIN KONG FINL HLDGS	Taiwan	Financials	2.43
ONGC IB	OIL & NATURAL GAS CORP	India	Energy	2.41
TNB MK	TENAGA NASIONAL	Malaysia	Utilities	2.35
MMI SJ	MMI HOLDINGS	South Africa	Financials	2.33
BBRI IJ	BANK RAKYAT INDONESIA	Indonesia	Financials	2.32
1288 HK	AGRI BANK OF CHINA H	China	Financials	2.28
OINL IB	OIL INDIA	India	Energy	2.13
KBANK TB	KASIKORNBANK	Thailand	Financials	2.11
000270 KS	KIA MOTORS CORP	South Korea	Consumer Discretionary	2.10
3988 HK	BANK OF CHINA H	China	Financials	2.05
096770 KS	SK INNOVATION CO	South Korea	Energy	2.03
1102 TT	ASIA CEMENT CORP	Taiwan	Materials	1.99
1800 HK	CHINA COMMUNIC CONSTRU-H	China	Industrials	1.99
029780 KS	SAMSUNG CARD CO	South Korea	Financials	1.95
PZU PW	POWSZECHNY ZAKLAD UBEZP.	Poland	Financials	1.93
BBAS3 BS	BANCO BRASIL	Brazil	Financials	1.91
3328 HK	BANK OF COMMUNICATIONS H	China	Financials	1.89
ITMG IJ	INDO TAMBANGRAYA MEGAH	Indonesia	Energy	1.88
HMCL IB	HERO MOTOCORP	India	Consumer Discretionary	1.87
1398 HK	ICBC H	China	Financials	1.87
001450 KS	HYUNDAI MARINE & FIRE IN	South Korea	Financials	1.85
004800 KS	HYOSUNG CORP	South Korea	Materials	1.83
BST MK	BERJAYA SPORTS TOTO	Malaysia	Consumer Discretionary	1.81
SISE TI	TURKIYE SISE VE CAM FAB.	Turkey	Industrials	1.80
024110 KS	INDUSTRIAL BANK OF KOREA	South Korea	Financials	1.80
INTP IJ	INDOCEMENT	Indonesia	Materials	1.80
2891 TT	CTBC FINANCIAL HOLDING	Taiwan	Financials	1.78
ECOPETL CB	ECOPETROL	Colombia	Energy	1.75
2009 HK	BBMG CORP H	China	Materials	1.75
902 HK	HUANENG POWER INTL H(HKD	China	Utilities	1.74
2883 HK	CHINA OILFIELD SVCS H	China	Energy	1.73
1101 TT	TAIWAN CEMENT CORP	Taiwan	Materials	1.72
2777 HK	GUANGZHOU R&F PROP H	China	Financials	1.71
ITSA4 BS	ITAUSA PN	Brazil	Financials	1.70
939 HK	CHINA CONSTRUCTION BK H	China	Financials	1.70

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 4: Best short ideas based on the machine learning model (N-LASR model) for MSCI EM universe

Ticker	Company Name	Country	GICS Sector	N-LASR Score (more negative = more likely to underperform)
1066 HK	SHANDONG WEIGAO GP MED H	China	Health Care	-2.86
ANG SJ	ANGLOGOLD ASHANTI	South Africa	Materials	-2.79
036570 KS	NCSOFT CORP	South Korea	Information Technology	-2.77
GENP MK	GENTING PLANTATIONS	Malaysia	Consumer Staples	-2.66
SIEM IB	SIEMENS INDIA	India	Industrials	-2.65
9933 TT	CTCI CORP	Taiwan	Industrials	-2.63
ECL CC	E-CL	Chile	Utilities	-2.52
220 HK	UNI-PRESIDENT CHINA HLDG	China	Consumer Staples	-2.42
3308 HK	GOLDEN EAGLE RETAIL GRP	China	Consumer Discretionary	-2.39
MFRISCOA MM	MINERA FRISCO	Mexico	Materials	-2.29
2707 TT	FORMOSA INT'L HOTELS	Taiwan	Consumer Discretionary	-2.29
257 HK	CHINA EVERBRIGHT INT'L	China	Industrials	-2.24
UBBL IS	UNITED BREWERIES	India	Consumer Staples	-2.23
BRML3 BS	BR MALLS PARTICIPACOES	Brazil	Financials	-2.20
URKA RX	URALKALI COMMON (RUB)	Russia	Materials	-2.18
068270 KS	CELLTRION	South Korea	Health Care	-2.16
2049 TT	HIWIN TECHNOLOGIES CORP	Taiwan	Industrials	-2.09
MULT3 BS	MULTIPLAN EMPREENDIM ON	Brazil	Financials	-2.07
1818 HK	ZHAOJIN MINING IND H	China	Materials	-2.01
011200 KS	HYUNDAI MERCHANT MARINE	South Korea	Industrials	-1.94
PTG MK	PETRONAS GAS	Malaysia	Utilities	-1.84
TMGH EY	TMG HOLDING	Egypt	Financials	-1.81
SNS PW	SYNTHOS	Poland	Materials	-1.80
TRU SJ	TRUWORTHS INTERNATIONAL	South Africa	Consumer Discretionary	-1.80
097950 KS	CJ CHEILJEDANG CORP	South Korea	Consumer Staples	-1.79
CLH CB	CEMEX LATAM HOLDINGS	Colombia	Materials	-1.77
PE&OLES* MM	INDUSTRIAS PENOLES CP	Mexico	Materials	-1.76
MSM SJ	MASSMART HOLDINGS	South Africa	Consumer Staples	-1.76
1044 HK	HENGAN INT'L GROUP CO	China	Consumer Staples	-1.75
6505 TT	FORMOSA PETROCHEMICAL CO	Taiwan	Energy	-1.73
PKS MK	PARKSON BHD	Malaysia	Consumer Discretionary	-1.72
086280 KS	HYUNDAI GLOVIS CO	South Korea	Industrials	-1.70
051900 KS	LG HOUSEHOLD & HEALTH	South Korea	Consumer Staples	-1.67
1314 TT	CHINA PETROCHEMICAL DEV	Taiwan	Materials	-1.66
CEMARGOS CB	CEMENTOS ARGOS (NEW)	Colombia	Materials	-1.66
1211 HK	BYD CO H	China	Consumer Discretionary	-1.66
ODPV3 BS	ODONTOPREV ON	Brazil	Health Care	-1.66
3697 TT	MSTAR SEMICONDUCTOR	Taiwan	Information Technology	-1.65
042670 KS	DOOSAN INFRACORE CO	South Korea	Industrials	-1.64
MPXE3 BS	ENEVA	Brazil	Utilities	-1.63

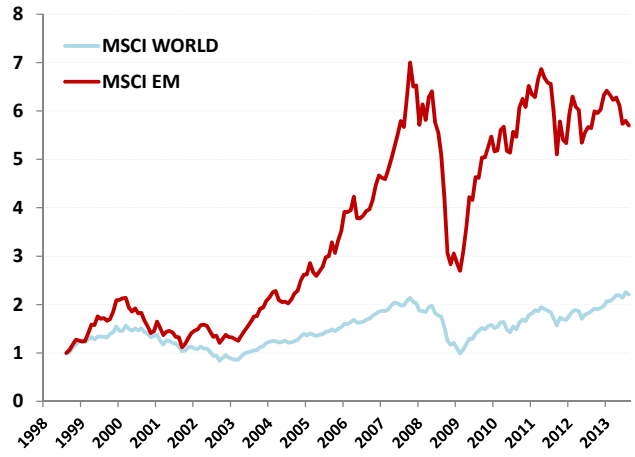
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

GEM overview

Recent challenges in emerging markets

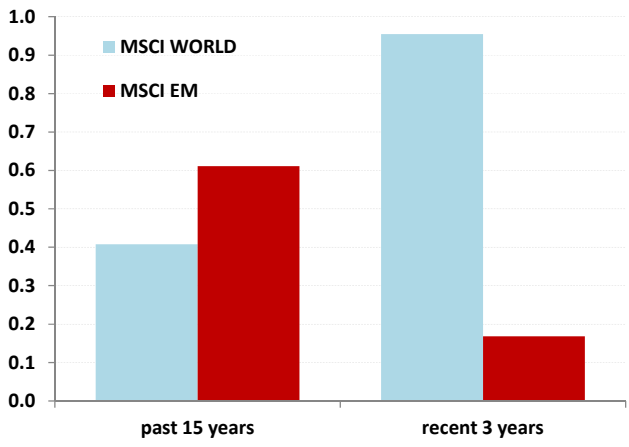
Over the long run, emerging markets have been growing much faster compared to developed markets. In the past 15 years, MSCI EM has generated more than twice as much return as developed markets (see Figure 5) with twice the Sharpe ratio (see Figure 6). However, the significant drawdowns during the global financial crisis and in recent months resulting from the concerns of FED tapering are also eye catching.

Figure 5: Performance of EM vs. DM



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 6: Sharpe ratio of EM vs. DM



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

After an 80% bounce back from the financial crisis in 2009, emerging markets gained less than 10% in the recent three and half years, in contrast to an over 40% return in the developed markets. The contrast between GEM and developed markets is more pronounced this year, as emerging markets plunged over -8% year to date, while developed market had a 15% increase.

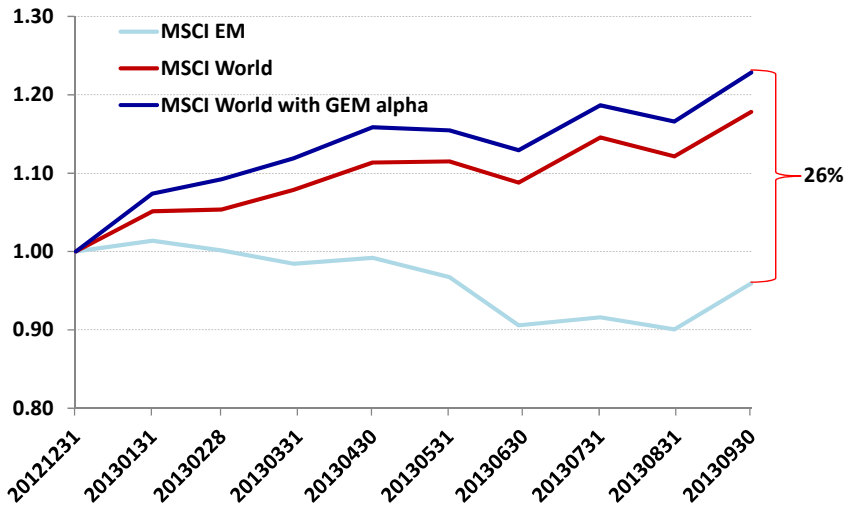
The GEM sell-off in the recent months is mainly due to the expectation that US Federal Reserve might cut its stimulus program of bond purchasing, known as tapering. This results in the liquidity concern in GEM. Some countries are better placed to deal with rising US interest rates than others. A number of emerging market currencies hit multi-year lows relative to US dollar. The countries with large current account deficits bear more of the selling pressure. For example, Brazil real, India rupee, Turkish lira and Indonesian rupiah have suffered over a 10% loss relative to US dollars this year. Furthermore, the risk of rising interest rates also has led some investors to wonder if the high economic growth in GEM can continue.

The slowing of economic growth in GEM is another reason for the outflows in many emerging market funds, especially due to the slowdown of the Chinese economy and the falling of materials and energy prices. The selling pressure in equity markets is further exacerbated by this weakness in commodities; further impacting GEM investors.

Separating alpha from beta

As quant investors in equity markets, we aim to separate alpha from beta. Figure 7 compares the performance of MSCI World (i.e. a pure beta strategy) with MSCI World plus a tilted GEM alpha strategy. Figure 7 shows the first eight months of 2013 when GEM had a 10% drawdown compared to a 12% return in DM. Investing in GEM alpha, we had more than a 3% excess return on top of the MSCI World. As such, for investors who do not want to have the broad GEM exposure, in this report we discuss how investors can generate DM beta alongside GEM alpha. As the figure below shows, this strategy performs significantly better than simply GEM beta (i.e. MSCI EM).

Figure 7: GEM alpha add value to MSCI World during the GEM selloff in 2013



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

GEM alpha

While GEM index products are popular and quite accessible, there are significant entry barriers for investors trying to access individual GEM stocks in their local markets. These challenges have had the effect of limiting the widespread implementation of rigorous stock-selection strategies, which might be the reason why we tend to see much more alpha opportunities in GEM.

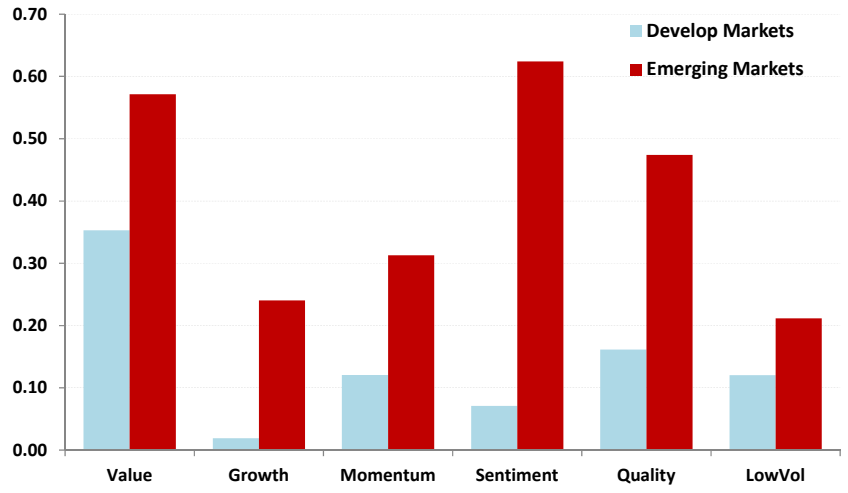
Figure 8 shows the long term average monthly rank IC of traditional quant factors for emerging markets compared with developed markets. Rank IC is essentially the correlation between the ranking of current factor scores and the ranking of forward stock returns in the following month. A factor with a higher rank IC means it has better predictive power of future stock returns[3]. In Figure 8, every style factor shows much better performance in emerging markets. For example, sentiment in DM is a mediocre factor, but it works very well in emerging markets.

Figure 9 and Figure 10 show the daily factor performance for emerging and developed markets in 2013. These figures show a simple long/short decile portfolio (buying the best decile and shorting the worst decile, equally weighted). Although the overall emerging market index performed much worse than developed markets this year, the magnitude of conventional style factor performance in GEM is higher than DM. This

[3] Please see Luo, et al [2009] DB Quant Handbook for details of our backtesting methodology.

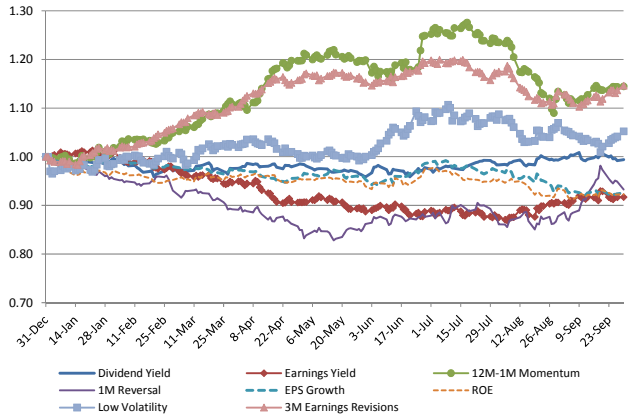
once again highlights that the alpha in GEM remains robust, despite the dip of the overall market.

Figure 8: Long term average rank IC from 1999 to 2013 for different styles of the factors in emerging markets and developed markets



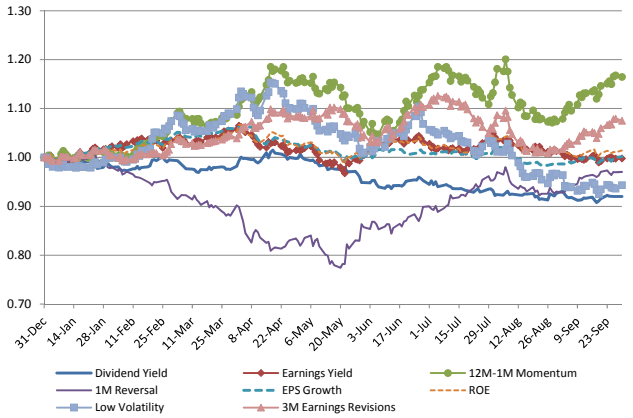
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 9: Daily factor performance of GEM YTD



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 10: Daily factor performance of DM YTD



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

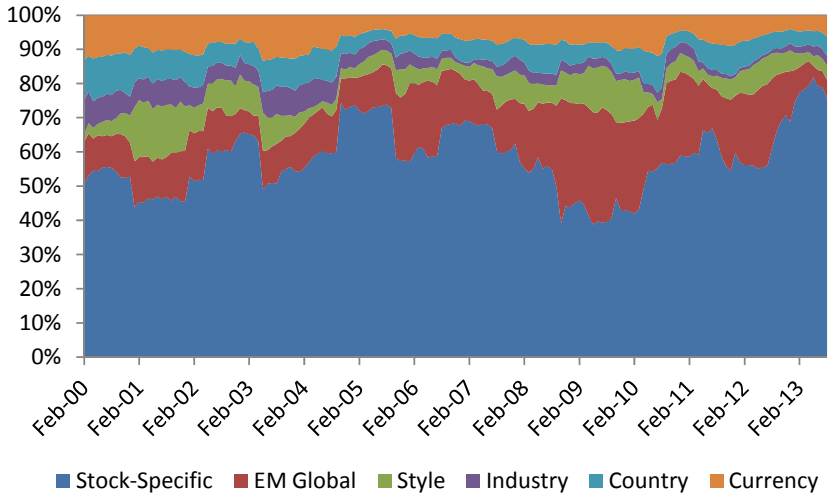
Opportunity set in GEM

Figure 11 shows the opportunity set[4] for emerging markets. We can think of this as the total alpha on the table. Our main interest is to understand what is driving that opportunity. The key is the size of the blue portion relative to the other colors. The blue color portfolio represents the opportunity explained by stock selection, whereas we can think of the other colors as the opportunities from top-down calls like picking the right countries, industries, and styles. When the financial crisis hit in 2008, we moved into a much more macro-dominated world. As a result, the portion of overall opportunity that could be explained by individual company characteristics shrunk sharply. However, since 2012, stock specific opportunity in emerging markets has risen quickly to all time

[4] Please see Alvarez, et al [2010, 2012] on how opportunity set is defined

highs. This means that the return available to stock selection strategies in GEM now is higher than ever.

Figure 11: Opportunity set in GEM

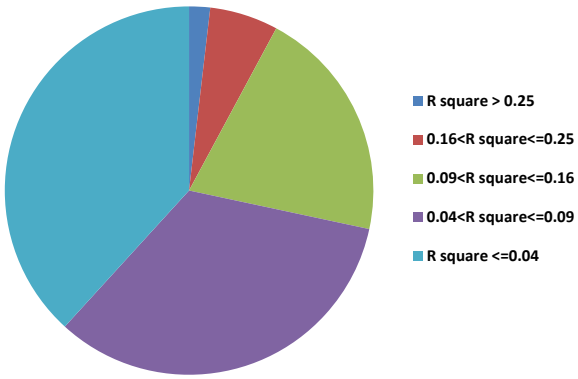


Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Emerging markets exposure

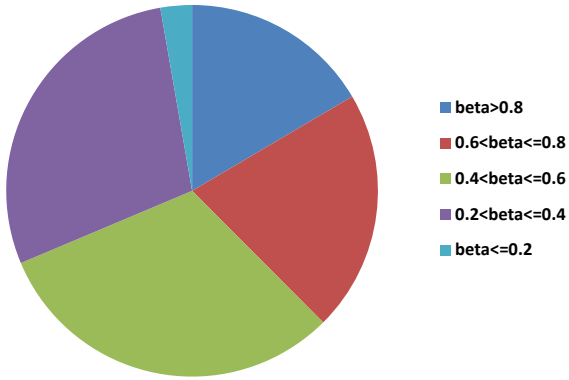
How much emerging markets exposure can we get from only investing in stocks in developed markets? For each stock in the MSCI World universe, we calculate its R squared and beta relative to the MSCI EM index. So essentially, we calculate the beta of stocks in the MSCI World universe to the MSCI EM index. Higher R squared means more of the stock return can be explained by MSCI EM market return. Figure 12 shows the current R^2 distribution of stocks in MSCI World. More than half of the stocks have R^2 less than 9%. This means most stocks in developed markets are not that sensitive to emerging market index, despite the fact that they may have large revenue or earnings exposures to GEM. Figure 13 shows the beta analysis for stocks in MSCI World. Higher beta means more exposure to the MSCI EM index. The majority of the stocks in the MSCI World index have beta lower than 0.6, which again suggests low GEM exposure.

Figure 12: MSCI World stocks' R^2 relative to MSCI EM index



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 13: MSCI World stocks' beta relative to MSCI EM index



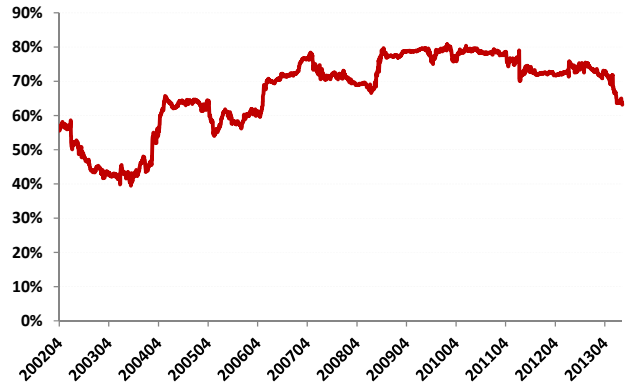
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

GEM as an asset class

In addition to the ample alpha opportunities, GEM also provides great diversification benefit to an overall global equity portfolio. Figure 14 shows the trailing one-year daily return correlation between MSCI World and MSCI EM index. The overall correlation ranges from 40% to 80%. Recently, it has dropped to 60%.

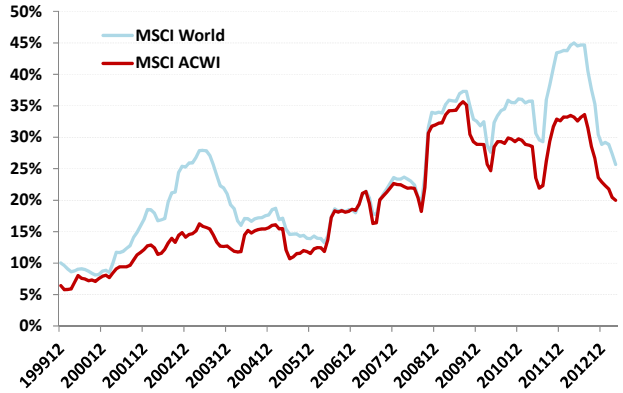
Figure 15 shows the weighted stock correlation in the MSCI World universe, compared with MSCI All Country universe. The weighted portfolio correlation is essentially the weighted pairwise correlation adjusted for asset volatility. Details of the definition of weighted portfolio correlation can be found in Luo, *et al* [2013a, 2013b]. By definition, MSCI ACWI (All Country) index is the combination of MSCI World and MSCI EM. By adding GEM stocks into the developed markets universe, the weighted stock correlation drops significantly. This once again highlights the potential diversification benefit of investing in GEM.

Figure 14: Correlation between MSCI EM and MSCI World



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 15: Weighted portfolio correlation



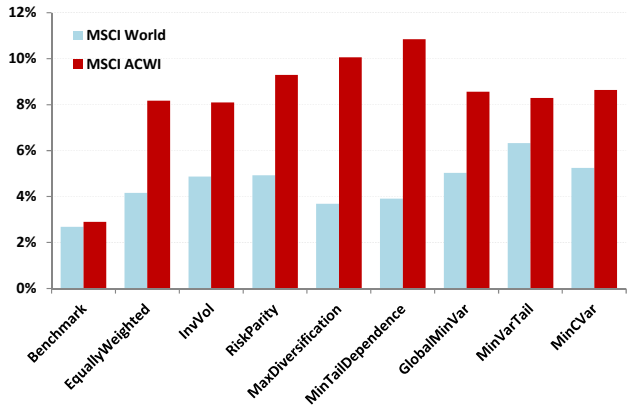
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Risk based country portfolios

Similar to Luo, *et sal.* [2013a, 2013b], we construct a series of risk-based country portfolios, using 24 developed country indices in the MSCI World, and then compare the performance to using all 45 countries (both developed and GEM). The backtesting begins from 2000 and ends in August 2013.

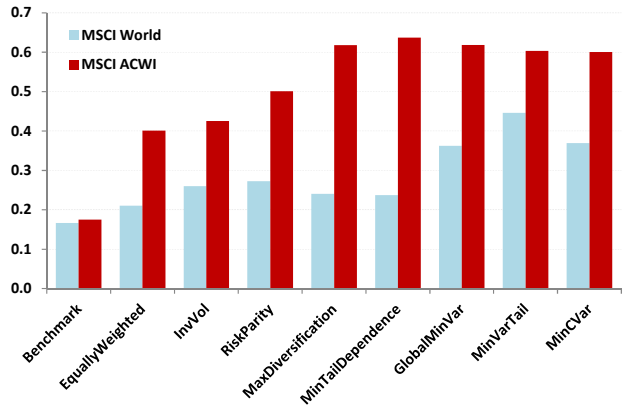
Figure 16 and Figure 17 show that the annualized returns and the Sharpe ratios using MSCI AC countries are significantly higher than the strategies using only developed countries. Figure 18 and Figure 19 show that by adding GEM, the average diversification ratios are higher and average weighted portfolio tail dependences (as another proxy for diversification and crowding) are lower. This means the risk is generally lower, and the portfolios tend to be more diversified. All in all, the addition of GEM results in better portfolios, regardless of the portfolio construction techniques.

Figure 16: Annualized return for different portfolio optimization techniques



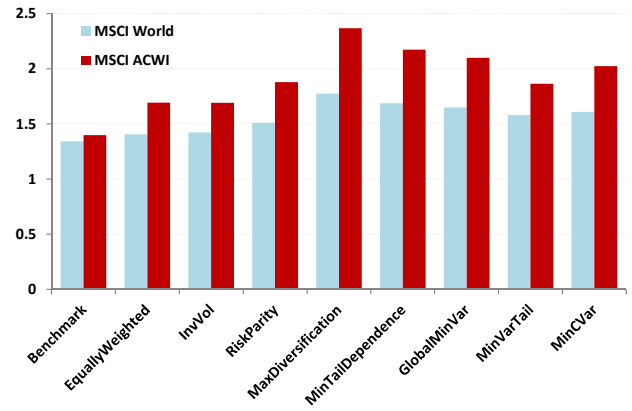
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 17: Annualized Sharpe ratio for different portfolio optimization techniques



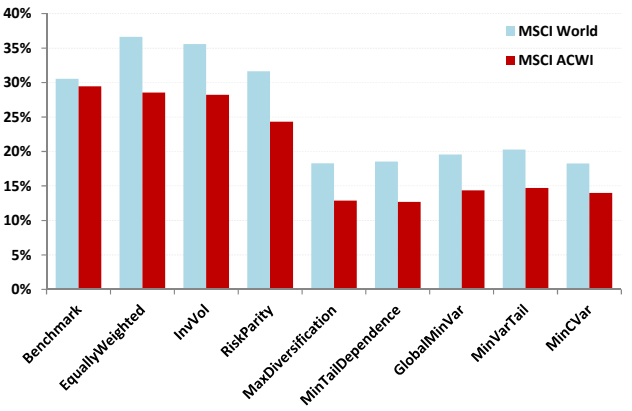
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 18: Average diversification ratio



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 19: Average weighted portfolio tail dependence



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

GEM microstructures

One of the biggest concerns for potential investors is that most GEM countries often have strict regulations and restrictions for foreign investors. These restrictions are often designed to protect local investors, and to reduce the amount of volatility in the markets. Here are some of the restrictions investors need to be aware of in order to invest in GEM:

- **Restriction on foreign ownership.** A country's government may decide to impose restrictions on foreign ownership to prevent outside investors from taking over a country's critical businesses. For example, in Russia, foreign citizens and legal entities are not allowed to own more than 25% of the capital of a Russian company. Another reason is to protect the economy from the volatility of short-term hot money trading. Foreign investors who invest heavily when market look attractive may also sell quickly when there are signs of trouble, which causes bubbles and crashes.

- **Restriction on short selling.** Short selling is often considered dangerous, thus, regulators in GEM are inclined to restrict short selling to reduce the undue selling pressure[5]. In 2002, 95% of developed countries allowed short sales, compared to 31% of emerging countries. The actual available inventory of stocks for lending/short-selling could be even lower — only 12% for emerging markets report that short-selling is feasible. For those emerging markets where short selling is indeed allowed, the cost is usually higher than developed markets. In addition, regulators in GEM are likely to restrict short selling at the first sign of trouble. Carefully working with prime brokers that understand local markets, with a deep inventory of stock lending pool, is critical to manage shorts in GEM.
- **Restriction on leverage.** Emerging markets usually have strict restrictions on leverage. The majority of institutional investors are only allowed to use minimal leverage, many times only temporarily, or no leverage at all.
- **Restriction in high frequency trading.** Although high frequency trading accounts for over 50% of US equity market trading volume, it is still limited in some emerging markets due to regulation and infrastructure.

Figure 20 summarizes some common microstructure issues for some of the major emerging market countries. Among them are the BRIC (Brazil, Russia, India, and China) countries — the largest economies GEM. We will discuss more details of those countries in the following section.

[5] Whether that is true or not, however, is subject to debates

Figure 20: Major equity emerging markets microstructure

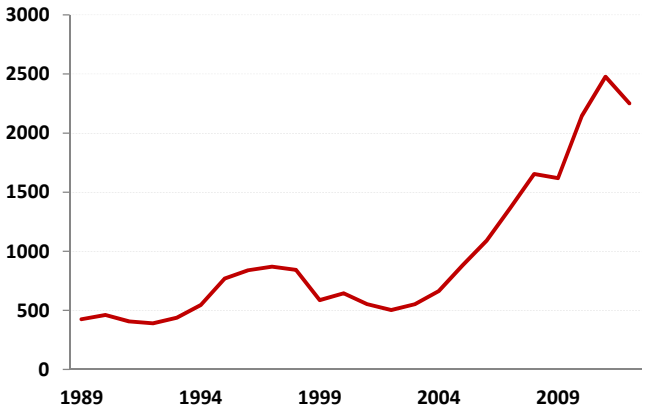
Country	Major Exchange	Trading Hours	Settlement Cycle	Is short selling allowed	Short selling conditions	Taxes on Dividends, capital gains	Ownership, foreign participation	Others
Brazil	BM&FBOVESPA	10:00 - 17:00 11:00 - 18:00 (Daylight saving)	T+3	Yes	Investors need to join the Securities Lending Program provided by BM&FBOVESPA	Taxes on Dividends : Exempt	Some sectors present threshold for foreign investors	
Russia	Moscow Exchange	9:30 - 19:00	T+2	Yes	Short sell only quoted securities	Dividends: 9% - residents; 15% - non-resident legal bodies; 30% - non-resident individuals	Foreign citizen and legal entities are not allowed to own more than 25% of the capital of a Russian company	
India	National Stock Exchange of India Limited Bombay stock Exchange	9:00 - 16:00	T+2	Yes	Rarely practiced	Dividend Income : Exempt	Individual foreign investors shall hold no more than 5% of the equity The combined holding of all foreign investors cannot exceed 49% of equity. Holdings of such through foreign direct investment shall not exceed 26%, and holdings of foreign institutional investors shall not exceed 23%	
China	Shanghai Stock Exchange; Shenzhen Stock Exchange	9:30 - 11:30 13:00 - 15:00	T+1 for A share T+3 for B share	Yes	Within the list of securities announced by stock exchanges	Total dividend held for: < 1 month: 20% income tax 1-12 month: 50% of the 20% income tax > 12 month: 25% of the 20% income tax.	Foreign securities institutions may directly participate in B shares. Qualified Foreign Institutional Investor allows licensed foreign investors to buy and sell A shares with limited quota.	Daily price fluctuation limits of stocks is 10%, and 5% for stocks under special treatment.
South Africa	Johannesburg Stock Exchange	09 :00 – 17 :00 (Reported Trades until 18:00)	T+5	Yes	Regulated covered short only		Virtually all business sectors are open to foreign investment. Certain sectors require government approval for foreign participation: energy, mining, banking, insurance, and defense.	
Taiwan	Taiwan Stock Exchange	9:00 - 13:30	T+2	Yes	Short selling of specific stocks	As for residents, dividends are included in the consolidated income. As for non-residents, 30% withholding tax for individuals ; 25% withholding tax for corporate beneficiary ; 20% withholding tax for foreign investor if the investment is approved by the Investment Commission	Most foreign ownership limits have been removed, except in a limited number of industries. On-shore foreign investors are subject to annual capital flow limits of US$5 million for an individual foreign investor and US$50 million for an unregistered foreign company.	Daily price fluctuation limits of stocks is 7%
Korea	Korea Exchange	9:00 - 15:00	T+2	Yes	No naked short selling	Dividends: 0~15.4% Capital Gains: 0	Almost no restrictions remain on foreign ownership of stock in Korean firms.	
Mexico	Bolsa Mexicana de Valores	8 :30 - 15 :00	T+3	Yes	Short selling can only be done on high and mid liquid stocks	Capital Gains : none Dividends : none	No person or group of persons will be able to acquire for more than 10% of the total shares of the Stock Exchange.	
Malaysia	Bursa Malaysia	9:00 - 17:00	T+3	Yes	Regulated short selling for list of selective stocks	Exempts single-tier dividend received by shareholders from tax.	Foreign ownership restriction for some sectors	
Indonesia	Indonesia Stock Exchange	9:30 - 16:00	T+3	Yes	Short selling is permitted only for certain shares announced by exchange every month.	Resident Individuals: maximum 10% of the final amount for dividend tax: Foreign companies: 15% of the gross amount for dividend tax:	Foreigners have good access to the Indonesian securities market. Foreign ownership of Indonesian companies may be limited in certain industries.	

Source: Bloomberg Finance LLP, Wikipedia, www.state.gov, www.world-exchanges.org, Deutsche Bank Quantitative Strategy

Brazil

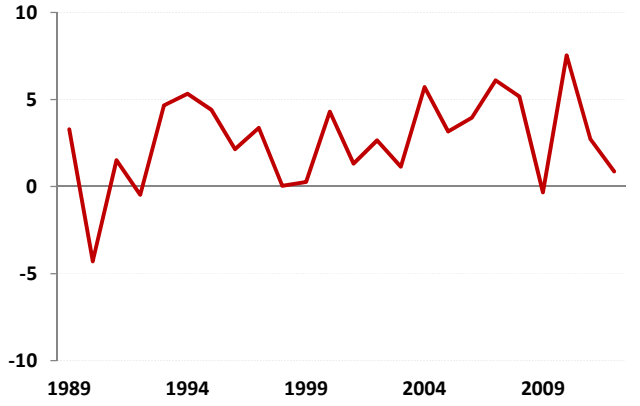
Brazil is the largest economy in Latin America, due to its rich natural resources and large labor pool. It is the world's sixth largest economy by normal GDP, and also currently of the fastest growing major economies in the world. Figure 21 shows the GDP level over time; and Figure 22 shows the GDP growth rate of Brazil for the same period. We can see that Brazil GDP has grown consistently at 4%-5% even in recent years.

Figure 21: Brazil GDP (Billion US$)



Source: World Bank, Deutsche Bank Quantitative Strategy

Figure 22: Brazil GDP growth (annual %)



Source: World Bank, Deutsche Bank Quantitative Strategy

Brazil has one of the most sophisticated stock exchanges in emerging markets called BM&F Bovespa. All trading in equity takes place at Bovespa on an order driven electronic trading platform called Megabolsa. Both individual and institutional investors can place orders directly into Megabolsa trading system through participating brokers. The order book is organized on best price/time priority. Settlement of all trades in the equity market takes place on T+3 day. Foreign investors have a few different ways to invest in Brazil stock markets. They can invest in the local market without any restriction, however, they need to hire local entities to act as custodians and representatives for regulatory and tax related issues. For placing orders on the stock exchanges, foreign investors need to select a BM&F Bovespa member brokerage firm. Most of the financial institutions located in Brazil provide such services to registration and investment under the same roof.

Foreign investors can also invest in the offshore investment available in the form of American Depository Receipts (ADRs), Global Depository Receipts (GDRs), and exchange traded funds (ETFs). The issuance of ADRs and GDRs by Brazilian companies must sign an agreement with the exchange in the other country. Typically, only large blue-chip companies have ADRs and GDRs. ADRs and GDRs usually have less liquidity compared with that trading in the local market. The easiest way to invest in the broad Brazil market is to use ETFs. ETFs are usually created to provide certain exposure to Brazilian stocks, and some ETFs serve benchmarks for actively managers.

Brazil permits short selling but imposes specific restrictions based on the citizenry of an investor. Foreign investors are required to have a legal representative stationed in Brazil in order to short sell. Security lending is done over the central counterparty which is BM&F Bovespa. Lenders and borrowers offers are registered in centralized system that is fully transparent. The central counterparty guarantees the settlement by conducting a centralized risk assessment of the participants and collateral they post to cover the risk.

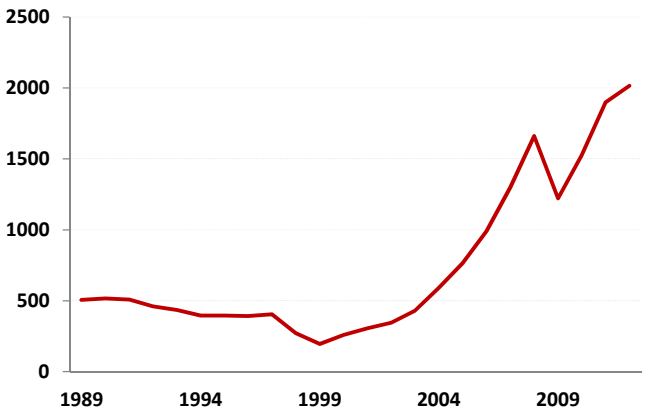
Collateral sufficiency is monitored real time and margin calls will be conducted for additional collateral, including intraday.

Finally, there are tax advantages for domestic investors in Brazil. International investors who invest in Brazil through National Monetary Council regulation 2689/2000 are taxed differently. Federal law grants advantages to these investors either by waving taxes or reducing the tax rate on their investments. There is no income tax on capital gains from transactions carried out in the local stock market for foreign investors. Foreign exchange transactions is the main tax that directly affects investment made by international investors, and can potentially be reduced.

Russia

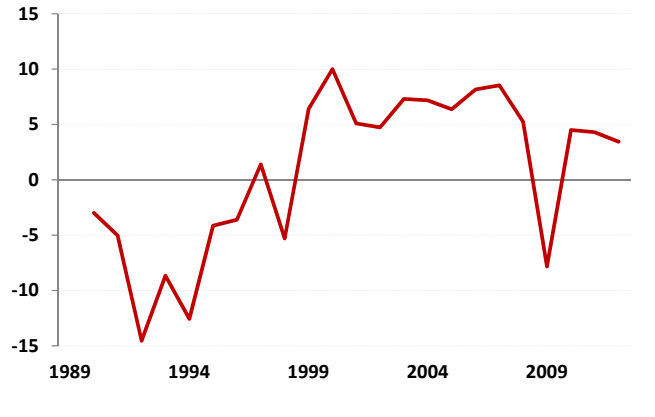
Russia is world's eighth largest economy by nominal GDP. It has rich natural resources including timber, precious metals, and particularly fossil fuels. In recent years, Russia's oil and gas export has been the primary source of economic growth. Russia experienced a 10 year rising of economy until hit by the financial crisis, and continues its stable 5% growth after 2010 (see Figure 23 and Figure 24). Since Russia entered the World Trade Organization in August 2012, the foreign investment climate has had some positive changes.

Figure 23: Russia GDP (Billion US$)



Source: World Bank, Deutsche Bank Quantitative Strategy

Figure 24: Russia GDP growth (annual %)



Source: World Bank, Deutsche Bank Quantitative Strategy

Moscow exchange is the largest stock exchange in Russia; and it is also in the world's top 20 exchanges by total market capitalization. It was created in December 2011 by the merger of two leading exchanges, MICEX and RTS. Settlement of all stock trades just switched from T+0 to T+2 days in September 2013. The equity market of Moscow Exchange has three market sectors:

- **Main Market** is the most liquid market where the trades are executed with the Central Counterparty. This is the major trading venue for international trading participants; and it accounts for 80% of the equity volumes. All trading in the Main Market sector is done through a modern electronic system.
- **Standard** is regulated market for stocks and fund shares where trades are made with the Central Counterparty. In addition to the main trading session, Standard sector has an evening trading session from 7pm to 11:50pm.
- **Classica** is the oldest securities market where trades are executed without full advance depositing of assets. Trading participants are allowed to negotiate the settlement terms and have the option to settle in US dollars.

Foreign investors can trade Russian stocks listed on foreign exchanges. The London stock exchange is the most popular place for Russian companies to dual list. There are also American Depository Receipts (ADRs) and ETFs which foreign investors can easily trade.

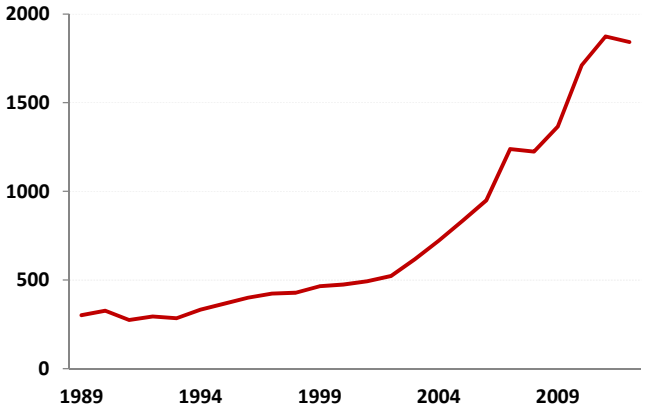
Short selling in Russia is regulated by a Russian federal executive body called Federal Financial Markets Service (FFMS). Brokers can trade stocks within the short sell list provided by each exchange according to the liquidity rules set by FFMS. During the financial crisis, because of the sharp drop in the Russian equity market, FFMS banned short selling, but subsequently lifted the ban in the middle of 2009.

In recent years, the Russian government has made a series of positive changes to the tax law making it more attractive to foreign investors. For example, starting in 2011, capital gains derived by foreign entities from the sale of shares in real estate related Russian entities are exempt from withholding tax. Tax reform continues to move forward in Russia, and it promises to bring the tax legislation closer to the needs of foreign investors.

India

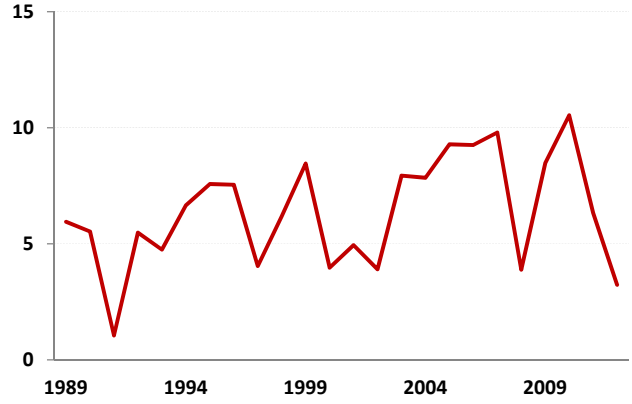
The Indian economy is the tenth largest in the world by nominal GDP and third largest by purchasing power parity (PPP). The population of India is the second largest in the world and over 50% of its population is below the age of 25 — a good indicator of long term growth. The GDP growth for India has stayed positive over the past 10 years (see Figure 25 and Figure 26).

Figure 25: India GDP (Billion US$)



Source: World Bank, Deutsche Bank Quantitative Strategy

Figure 26: India GDP growth (annual %)



Source: World Bank, Deutsche Bank Quantitative Strategy

Most of the Indian stocks are traded over the main exchanges: National Stock Exchange (NSE) and Bombay Stock Exchange (BSE). Both exchanges have the same trading mechanism, trading hours and settlement process. Almost all the big firms in India are listed on both exchanges. The trading systems for both exchanges are fully automated and adopt the principle of order driven market. Market orders placed by investors are automatically matched with the best limit orders. It is transparent, but there is no guarantee that an order will be executed. Institutional investors can place orders directly into the stock market trading system through the direct market access (DMA) option provided by brokers. Equity trading follows a T+2 rolling settlement.

There are two categories of foreign investments in India: foreign direct investment (FDI) and foreign portfolio investment (FPI). Most of the equity investments are classified as

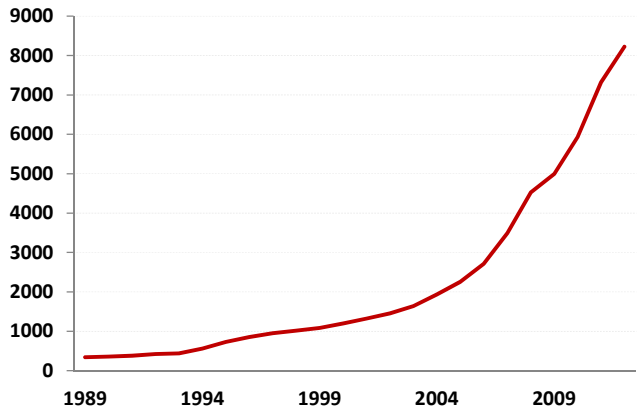
FPI; and therefore foreign institutional investors need to register with the market regulator. Foreign institutional investors and their sub accounts can invest in any stocks listed in India, but must use special non-resident rupee bank accounts in order to move money in and out of India. Previously, foreign individuals are not allowed to invest directly into the stock market in India. In 2012, central government decided to allow individual qualified foreign investors (QFIs) to invest up to 5% of the paid-up capital of a listed company. Foreign investors can also invest through offshore instruments such as ADRs, GDRs and ETFs. However, many large Indian firms do not yet have ADRs or GDRs that are available to offshore investors.

Short selling is allowed in India, but rarely practiced. Only a limited set of stocks traded in the futures and options markets are allowed to be borrowed and lent. In addition, naked shorting is not permitted. The Securities and Exchange Board of India (SEBI) recently said it would allow stocks that meet several criteria, including average monthly turnover over at least 1 billion rupees to be used under the country's securities lending and borrowing (SLB) program. This should increase the number of stocks that are allowed for short selling.

China

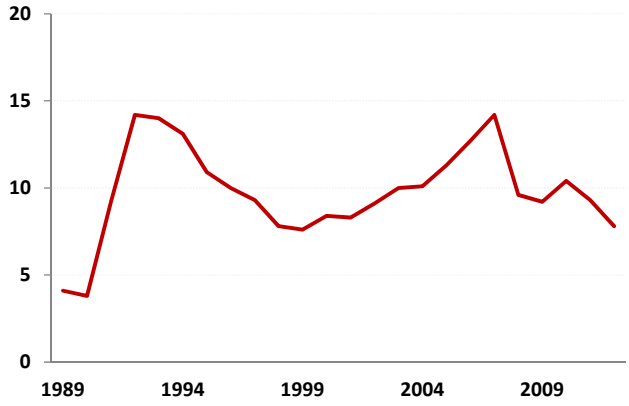
China is the world second largest economy by nominal GDP and by purchasing power parity. It's the world fastest growing major economy in the past 30 years. It's the largest exporter and second largest importer of goods in the world. Figure 27 shows the GDP level for China since 1989; and Figure 28 shows the GDP growth rate of China for the same period. China's GDP has been growing at an average rate of over 10% over the entire period.

Figure 27: China GDP (Billion US$)



Source: World Bank, Deutsche Bank Quantitative Strategy

Figure 28: China GDP growth (annual %)



Source: World Bank, Deutsche Bank Quantitative Strategy

Shanghai stock exchange and Shenzhen stock exchange are the two main stock exchanges in mainland China. Securities are traded on both exchanges on a market driven and free auction basis. Limit orders and market orders are accepted in line with market conditions. There is a 10% daily price up and down limit, except for the first trading day, special treatment shares are subject to a 5% daily price up and down limit. Investors have to wait until the following day to transact. There are two types of stocks issued in Shanghai and Shenzhen stock exchanges.

- **A shares** are priced in local RMB currency and restricted to domestic investors.
- **B shares** are priced in US dollar and available to both domestic and foreign investors.

Foreign investors are allowed (with limits) to trade in A shares under the QFII (Qualified Foreign Institutional Investor) program launched in 2003. In December 2011, RQFII (Renminbi Qualified Foreign Institutional Investor) was introduced that allows overseas investors to use offshore RMB deposits to invest in mainland securities markets. In 2012 and 2013, China further increased the total quotas for QFII and RQFII twice, from US$30 billion to US$150 billion, and RMB20 billion to RMB270 billion, receptively. In addition, QFII qualification requirements were relaxed recently. For example, institutional investors who used to need five years of experience with AUM greater than US$5 billion, now only need two years experience and AUM greater than US$500 million. The implication of Opening A-shares to global investor could be significant. In June 2013, MSCI announced the start of reviewing China A-shares for potential inclusion in MSCI EM index. If A-shares were to be included, China A-shares and China as a whole would represent up to 14% and 30% of the MSCI EM Index, respectively.

In addition to the A and B shares listed in China, there are a few more types of shares for Chinese companies listed in other stocks exchanges:

- **H shares** are companies incorporated in mainland China but listed in Hong Kong, and denominated in Hong Kong dollars. H-shares are still regulated by Chinese law but trade the same as other stocks listed in Hong Kong exchanges. It accounts for more than half of the Chinese stocks available for foreign investors.
- **Red Chip** refers to Chinese companies incorporated outside mainland China and listed in Hong Kong. These businesses are mainly based in mainland China and controlled by Chinese government. It's the second largest portion of Chinese stocks available for foreign investors.
- **P Chip** refers to Chinese companies listed in Hong Kong incorporated in the Cayman Island, Bermuda and British Virgin Islands with operations in mainland China, and are run by Chinese private sectors.
- **N Shares, S Shares and L Shares** refer to Chinese companies listed in the US, Singapore and London respectively.

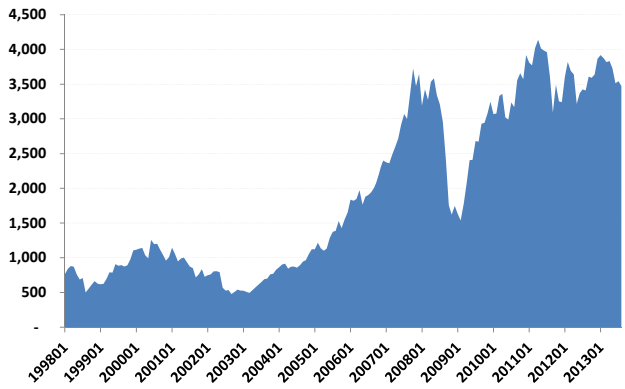
Short selling is very limited in China, with a small number of companies approved by the exchanges. In practice, few institutional investors short sell individual companies in China due to the limited inventory that can be borrowed and the cost can be very high. However, China is relaxing short-selling restrictions. In February 2013, China launched the pilot program to allow a handful number of brokerage firms to borrow shares from institutional investors for use in short selling.

MSCI EM: an investable universe

For foreign investors who want to invest in GEM equities, the MSCI EM universe is the most widely used benchmark. MSCI EM index is part of the MSCI standard indices that composed of the MSCI Large Cap and Mid Cap indices. It is based on the MSCI Global Investable Market Indices methodology, weighted by the float market cap of each stock in the universe. Therefore, it is easy to track and truly investable. There are also tradable MSCI EM ETFs and futures that track the index. Therefore, in the rest of this paper, we will discuss strategies based on this universe.

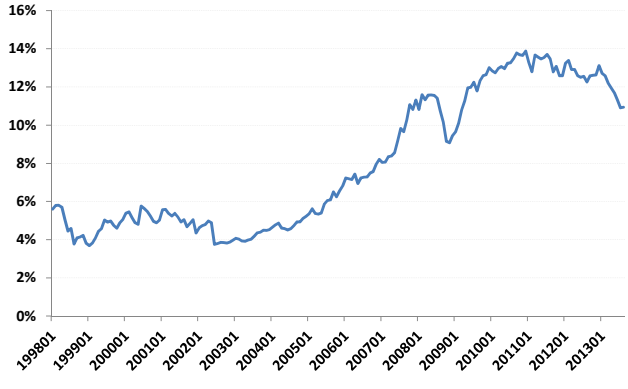
The total market cap for MSCI EM has increased dramatically over the past 15 years (see Figure 29), along with its share in the world — MSCI ACWI (see Figure 30).

Figure 29: Total Market Cap for MSCI EM (billion USD)



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 30: MSCI EM weight in the MSCI All Country



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Traditional quant factors in GEM

In this section, we study how traditional quant factors perform in GEM. We classify these factors into six different styles categories: value, growth, momentum/reversal, sentiment, quality and low vol. We build a composite factor for each style based on some of the most commonly used factors. At this stage, we do not intend to identify the best stock selection factors, but to show how each style behaves in GEM. For simplicity, we equally weight the factors in each style bucket. We examine how each style performs in different countries and discuss some interesting patterns. We will address factor weighting issues in the next section.

Value

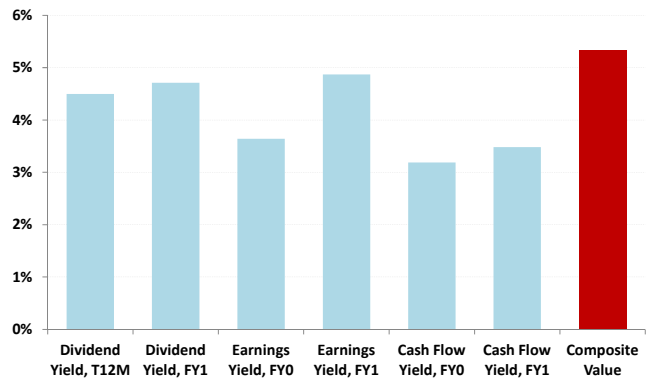
Earnings yield, dividend yield and cash flow yield are three well known value factors. For each factor we consider both trailing yields and forward yields based on IBES consensus. Figure 31 shows the time series performance correlation. Most factors are actually not highly correlated, suggesting potential diversification benefit. We build the composite value factors by equally weighting the above six value factors. As expected, the average rank IC and the risk adjusted rank IC[6] of the composite value factor are higher than each of the individual factors (see Figure 32 and Figure 33).

Figure 31: Correlation among the value factors

	Dividend Yield, T12M	Dividend Yield, FY1	Earnings Yield, FY0	Earnings Yield, FY1	Cash Flow Yield, FY0	Cash Flow Yield, FY1
Dividend Yield, T12M	100%					
Dividend Yield, FY1	83%	100%				
Earnings Yield, FY0	32%	38%	100%			
Earnings Yield, FY1	8%	31%	79%	100%		
Cash Flow Yield, FY0	19%	26%	43%	42%	100%	
Cash Flow Yield, FY1	1%	24%	62%	80%	64%	100%

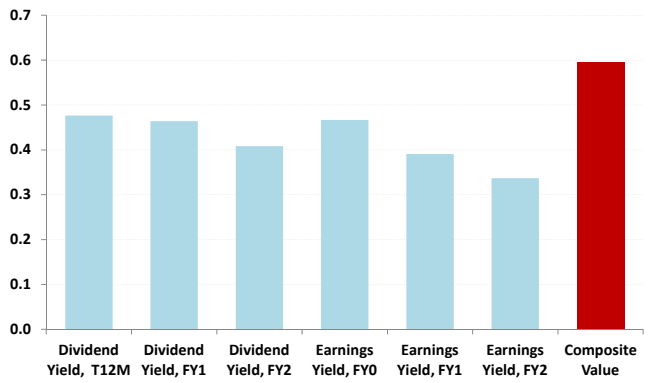
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 32: Average rank IC for the value factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 33: Risk adjusted rank IC for value factors

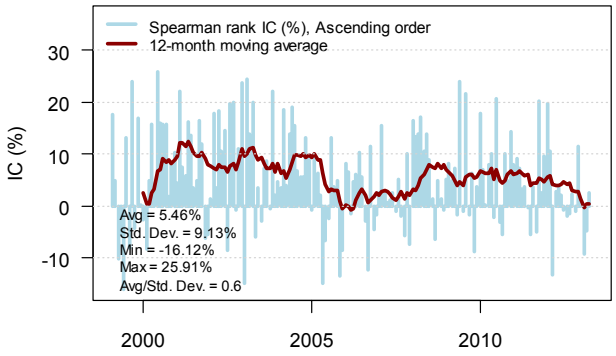


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

[6] The risk adjusted rank IC is defined by the average rank IC divided by the standard deviation of the rank IC.

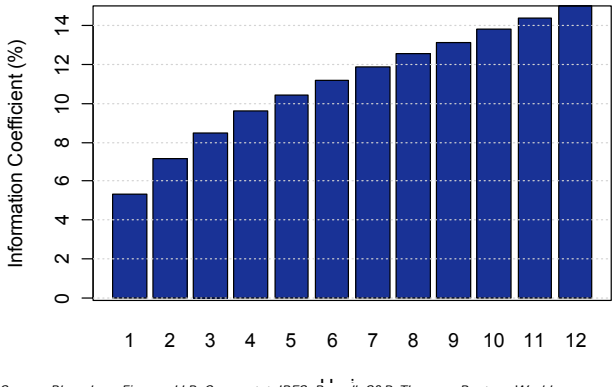
Figure 34 shows the time series rank IC of the composite value factor. Value tends to be one of the best performing factors in GEM. The 12 month average performance has remained almost always positive. Even during the financial crisis, value still survived well. Figure 35 shows the cumulative IC decay for the composite value factor. As expected, value is a slow decay factor. The predictive power increases as we expand the forecasting horizon.

Figure 34: Time series of rank IC for composite value factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

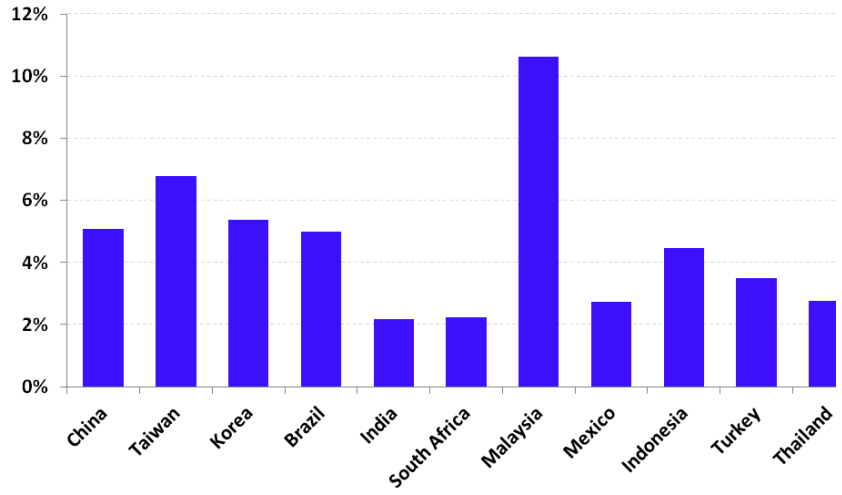
Figure 35: Cumulative IC decay for composite value factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 36 shows the performance of the composite value factor in major GEM countries. We include all the countries that have over 20 stocks in the universe with at least 10 years of history. Value factor performs well in most countries, especially in Malaysia, Taiwan, and China.

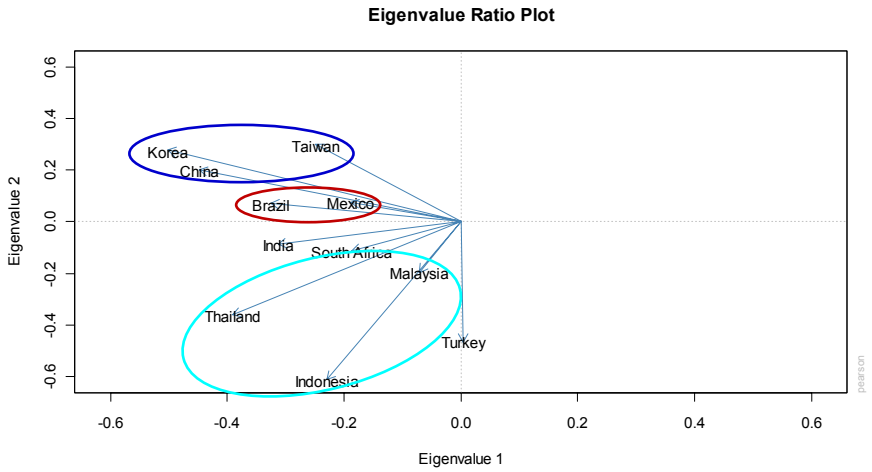
Figure 36: Average rank IC of value factor for different countries



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

We can cluster major GEM countries by how value factor performs, using eigenvalue ratio analysis (see Luo, *et al* [2013a] for details). The country clustering analysis is quite intuitive (see Figure 37) — those countries that are grouped together usually have similar culture and geographic location, and are economically dependent on each other. For example, China, Taiwan, and Korea form the East Asia cluster, while Mexio and Brazil are more closely related to each other.

Figure 37: Grouping the countries by value factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Growth

Investors typically associate high growth with emerging markets. Therefore, growth factors are also often perceived as best stock selection signals. The results, however, are rather disappointing. Although growth factors are not highly correlated to each other (see Figure 38), the average performance of most growth factor is less than a third of value factors (see Figure 39 and Figure 40). Our composite growth factor does show some modest improvement over the three comprising factors.

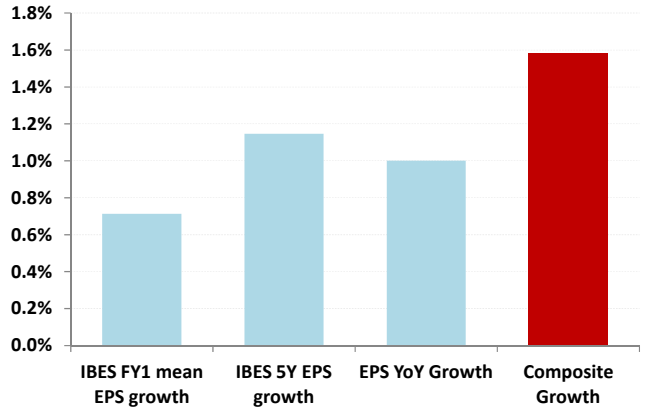
Figure 41 shows the time series of rank IC for the composite growth factor. We can see that growth performed well before the final crisis, but collapsed during the financial crisis. In recent years, growth started to pick up the steam again. Unlike value, the growth factor is a fast decay factor (see Figure 42). The cumulative performance falls quickly after four months.

Figure 38: Correlation among the growth factors

	IBES FY1 mean EPS growth	IBES 5Y EPS growth	EPS YoY Growth
IBES FY1 mean EPS growth	100%		
IBES 5Y EPS growth	34%	100%	
EPS YoY Growth	2%	41%	100%

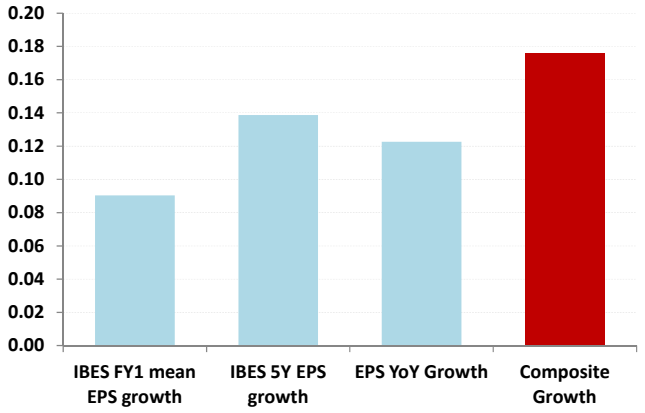
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 39: Average rank IC for the growth factor



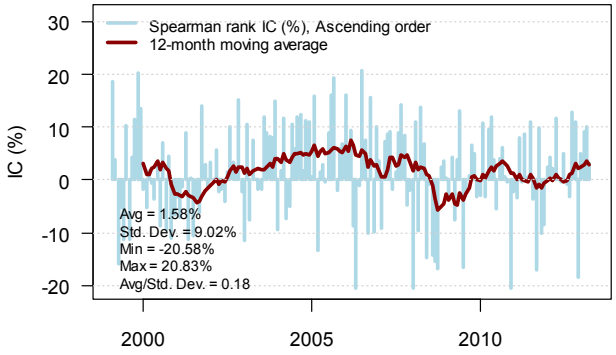
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 40: Risk adjusted rank IC for growth factors



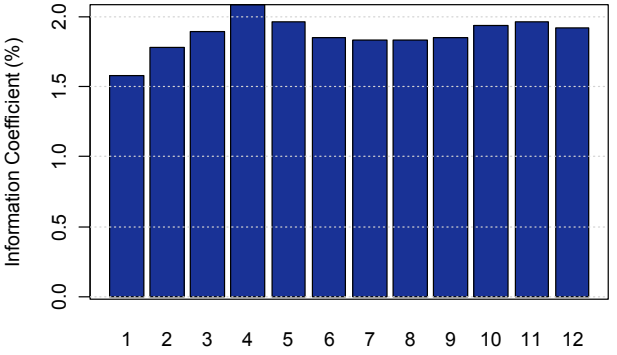
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 41: Time series of rank IC



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

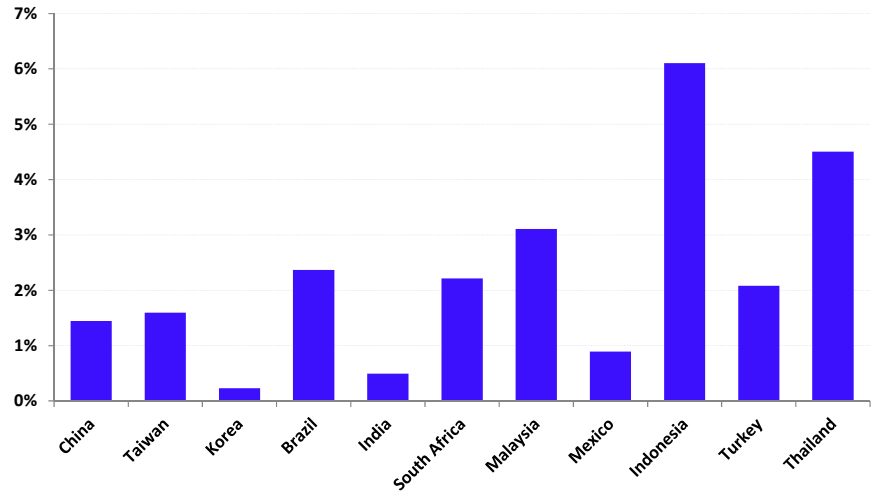
Figure 42: Cumulative IC decay



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 43 shows the average rank IC of our composite growth factor in the major GEM countries. Overall, growth is not as strong as value. It works well in Malaysia, Indonesia and Thailand — Southeast Asian countries. These countries are also closely connected to each other. On the other hand, growth factors have been essentially noises in Korea, India, and Mexico.

Figure 43: Average rank IC of growth factor for different countries

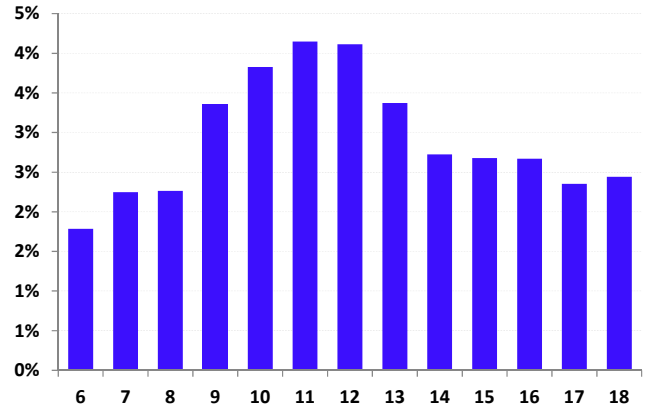


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Momentum

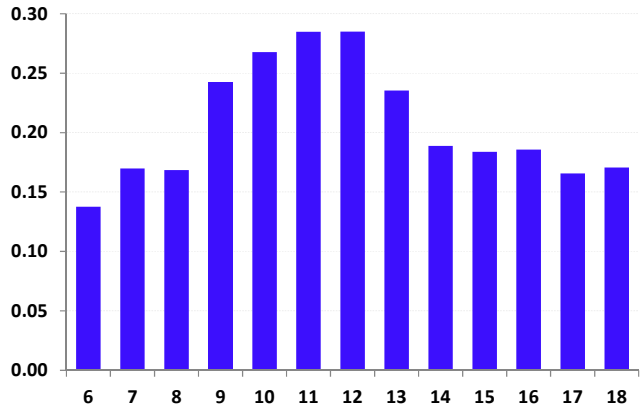
Along with value, momentum has been widely publicized. Typically, we use price return over the previous 12 months excluding the most recent month to construct the momentum factor. It is interesting to check the "optimal" price momentum formation period. It turns out our traditional 12 minus one month momentum does perform well (see Figure 44 and Figure 45). Therefore, to keep it consistent we use this as our momentum factor.

Figure 44: Average rank IC for different horizon (n month) of momentum, defined as returns in previous n month minus the recent month



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

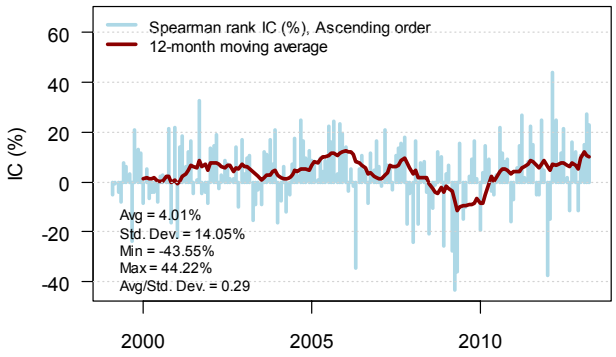
Figure 45: Risk adjusted rank IC for different horizon (n month) of momentum, defined as returns in previous n month minus the recent month



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

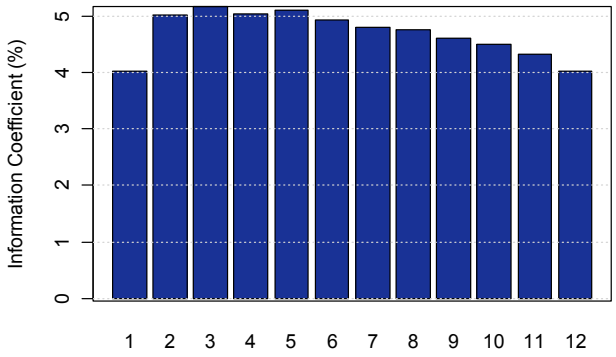
Similar to how momentum factor performed in developed markets, it also had a big drawdown during the risk rally subsequently to the global financial crisis. Figure 47 shows the cumulative IC decay for the momentum factor. As expected, momentum also decays quickly.

Figure 46: Time series of rank IC of momentum factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

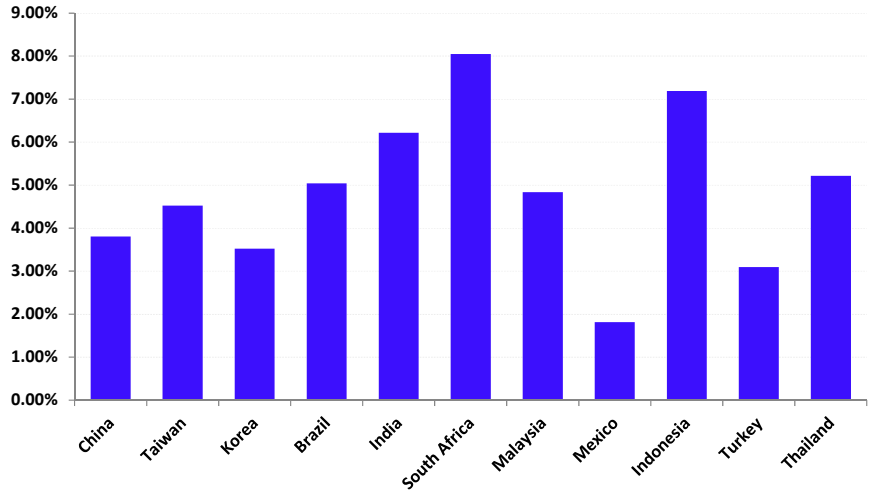
Figure 47: Cumulative IC decay of momentum factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 48 shows the average performance of the momentum factor across the major GEM countries. Similar to value, momentum demonstrates strong performance that is robust to economic development and geographic location.

Figure 48: Average rank IC of momentum factor for different countries

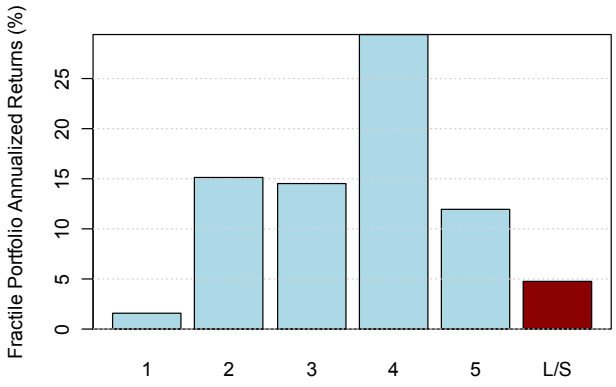


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

A case study – momentum in China and India

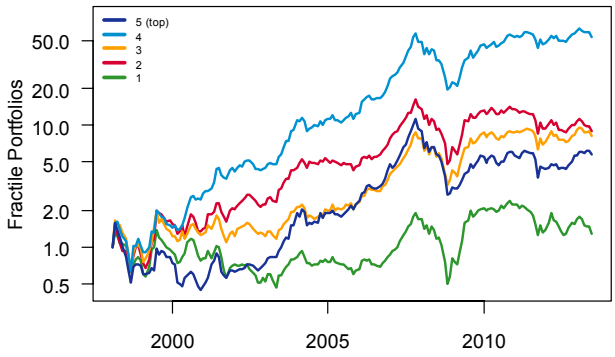
Figure 49 and Figure 50 show the performance of the five quintile momentum portfolios in China. Interestingly, the top quintile is not necessarily the best. Rather the second best quintile outperforms everything else significantly. It produces almost twice as much return as the second best performing quintile (i.e., quintile two). The AdaBoost algorithm used in our N-LASR stock selection model can easily capture these types of non-linear relationships (see Wang, *et al* [2013] for details).

Figure 49: Quintile portfolio annualized return for China



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

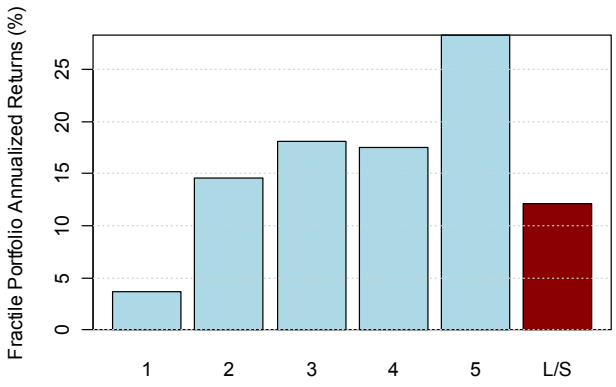
Figure 50: Quintile cumulative return for China



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

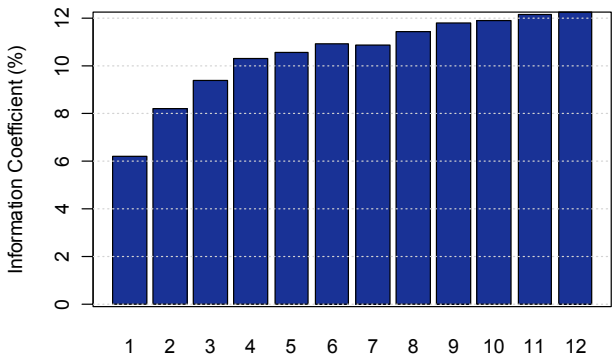
Now let's look at the momentum factor in India. In contrast to China, the performance is indeed mostly monotonic (see Figure 51). Figure 52 shows the cumulative IC decay in India. Compared with momentum in the broad emerging markets (Figure 47), India momentum decays much slower. This once again highlights the countries in GEM can be very different and require different modeling techniques.

Figure 51: Quintile portfolio annualized return for India



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 52: Cumulative IC decay for India

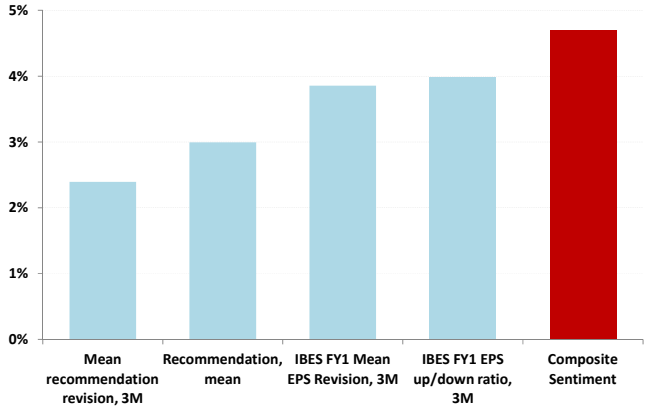


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Sentiment

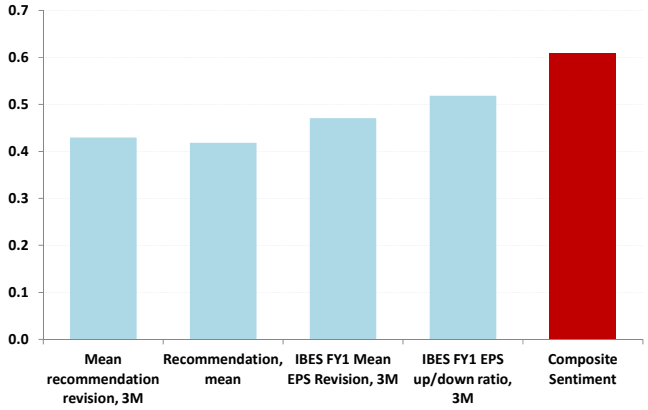
In the quant dashboard (Figure 9) we witnessed the outperformance of earnings revisions in emerging markets — the most stable quant factors in GEM this year. In this section, we construct a composite sentiment factor based on four commonly used factors: mean recommendations, recommendation revisions, earnings revisions, and earnings diffusion ratios (see Figure 53 and Figure 54). The composite factor again shows some diversification benefit and outperforms the underlining factors.

Figure 53: Average rank IC for the sentiment factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

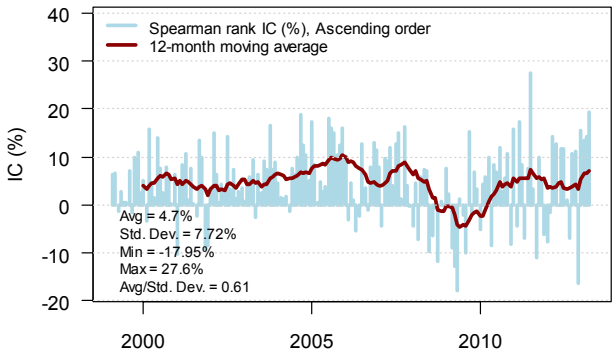
Figure 54: Risk adjusted rank IC for sentiment factors



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

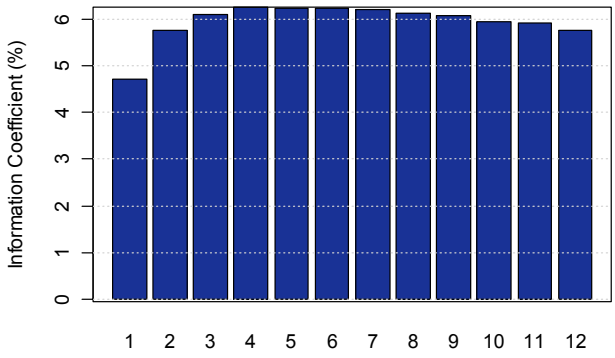
The composite sentiment factor performs well most of the times (see Figure 55). The only major drawdown was during the financial crisis. Figure 56 shows the cumulative IC decay for the sentiment factor. The one month predictive power of the sentiment composite is comparable to value (Figure 35), but value factor has slower decay. Sentiment composite needs to turnover more quickly than the value factor in order to adequately capture its performance.

Figure 55: Time series of rank IC of sentiment factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

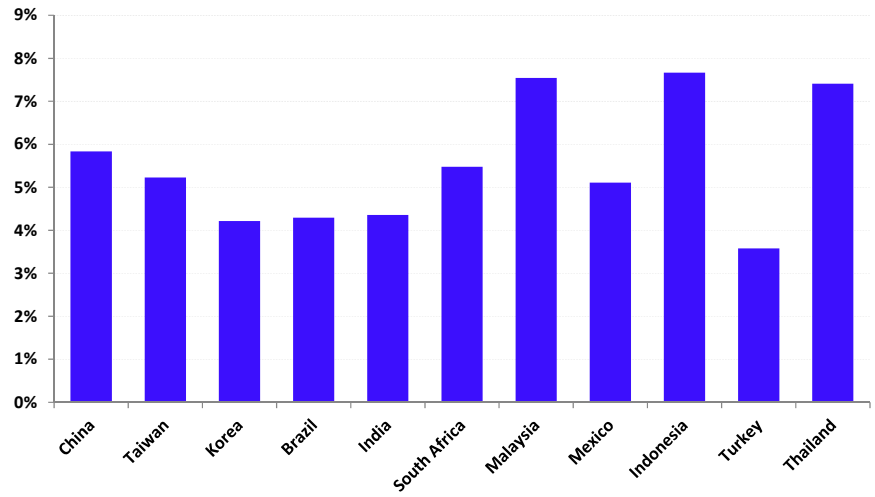
Figure 56: Cumulative IC decay of sentiment factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 57 shows the average performance of the composite sentiment factor in the 11 major emerging market countries. We see that the sentiment factor generally performs well across all countries. Again, Malaysia, Indonesia and Thailand show up as the top three countries with the highest average rank IC.

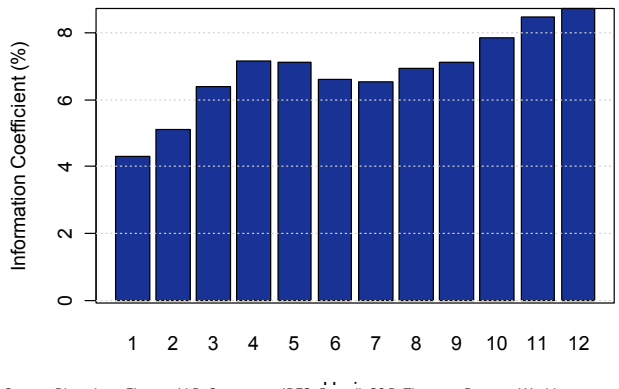
Figure 57: Average rank IC of sentiment factor for different countries



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

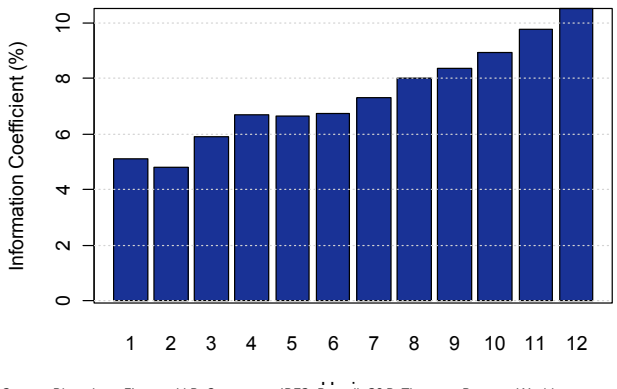
Another finding is that if we group the countries by IC decay pattern, they cluster quite intuitively by region: Brazil and Mexico have slow IC decay (see Figure 58 and Figure 59). China and Korea have slightly faster decay (see Figure 60 and Figure 61), while Malaysia and Thailand have very quick decay (see Figure 62 and Figure 63). This probability due to the fact that EM sell side analysts are more regionally based.

Figure 58: Cumulative IC decay for Brazil



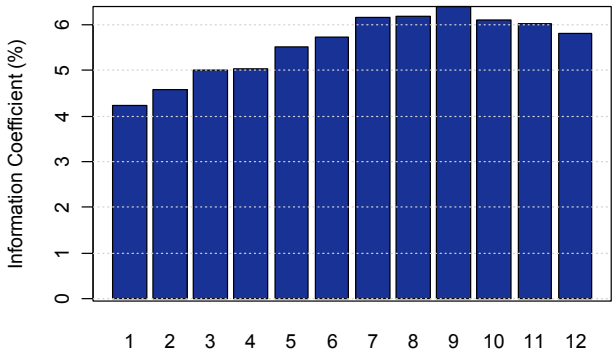
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 59: Cumulative IC decay for Mexico



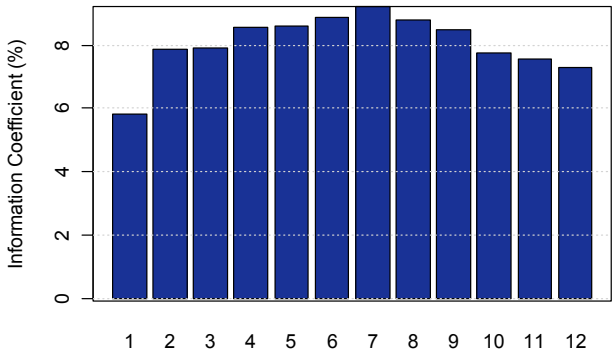
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 60: Cumulative IC decay for Korea



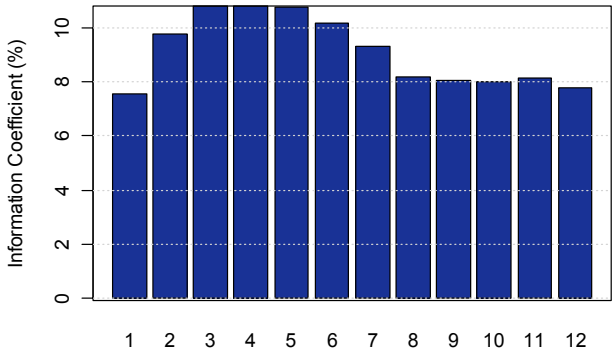
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 61: Cumulative IC decay for China



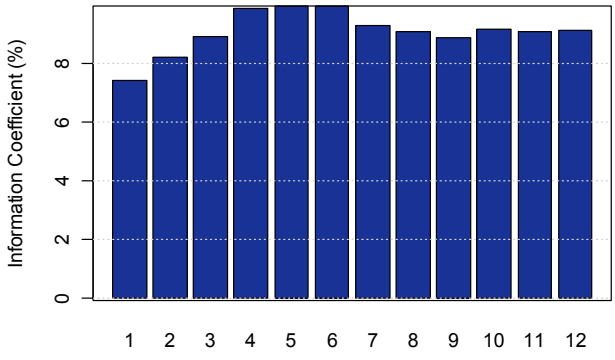
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 62: Cumulative IC decay for Malaysia



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 63: Cumulative IC decay for Thailand



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

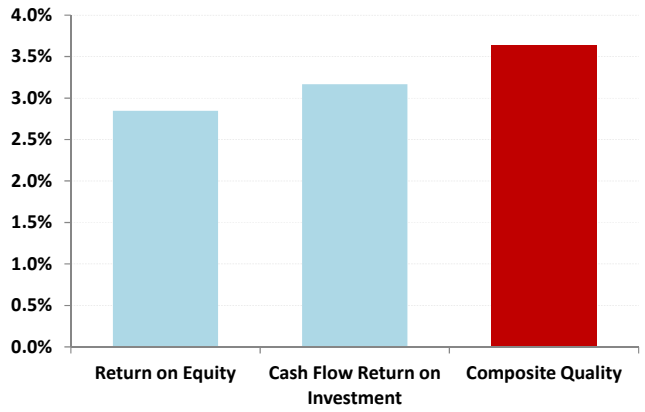
Quality

For quality factors, we use return on equity (ROE) and cash flow return on investment (CFROI) as two examples. The CFROI has several different definitions (e.g., Nicoletti [2004] and Venanzi [2010]). We define CFROI as:

$$CFROI = \frac{\text{cash flow}}{\text{market value investment}}$$
$$= \frac{\text{cash flow from operations}}{\text{total asset - total book value of equity + total market cap of equity}}$$

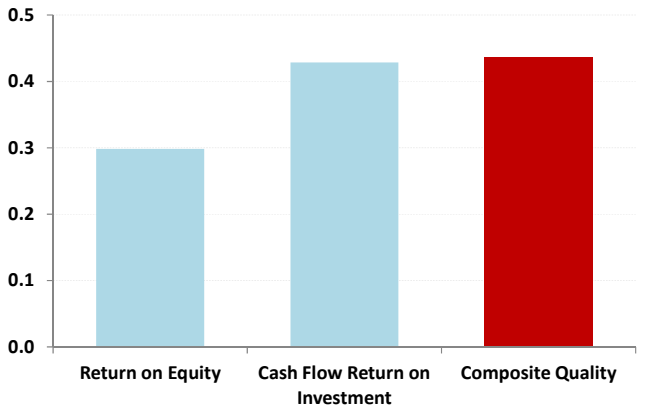
We equally weight ROE and CFROI factors to construct the composite quality factor. As shown in Figure 64 and Figure 65, CFROI has slightly better performance than ROE, and the composite quality factor outperforms each individual factors.

Figure 64: Average rank IC for the quality factors



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 65: Risk adjusted rank IC for quality factors

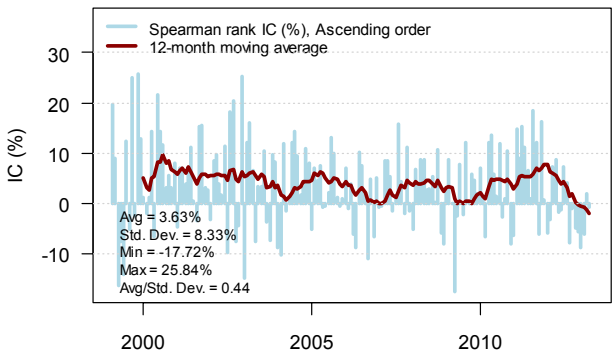


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Unlike most other factors, the quality composite survived well during the financial crisis, but has shown strong decay in recent years (see Figure 66). Similar to value factors, quality factors also tend to be slow decay factors (see Figure 67).

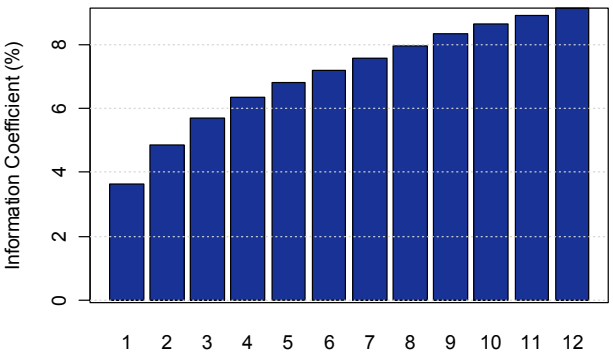
Our composite quality factor performs well in Taiwan, Malaysia, Indonesia and Brazil, but not so much in other GEM countries (see Figure 68).

Figure 66: Time series of rank IC of quality factor



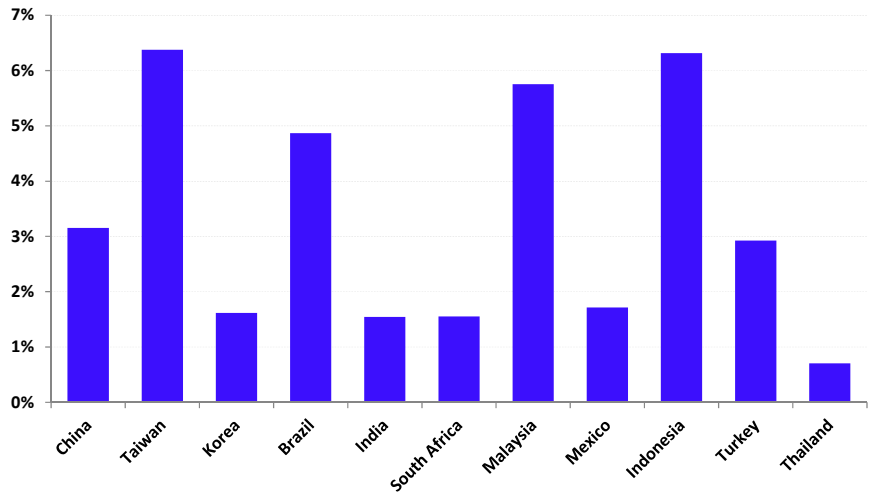
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 67: Cumulative IC decay for the quality factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 68: Average rank IC of quality factor for different countries

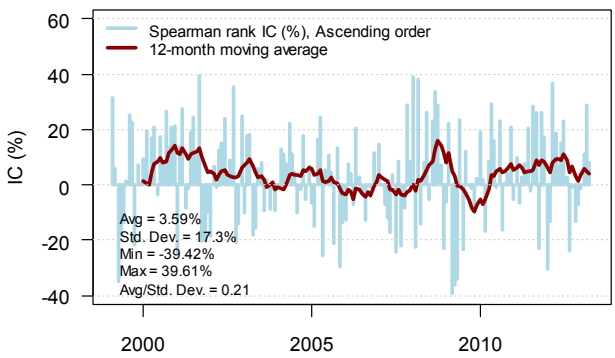


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Low Vol

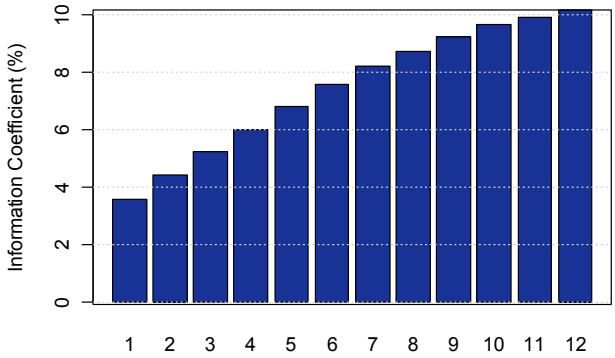
The Low volatility anomaly is an interesting phenomenon in equity markets. Classic finance teaches us that higher risks should be compensated with higher expected returns. However, empirically, low volatility stocks often deliver higher returns than riskier stocks. We discussed this anomaly in our previous research papers (Cahan, *et al* [2012a, 2012b], Luo, *et al* [2013a]). Now, let's see how low vol, as a factor, performs in GEM. We use the daily realized volatility using trailing one year window as our low vol factor. We can see that on average lower volatility stocks do indeed outperform riskier stocks (see Figure 69). However, the performance can be quite volatile. The performance of the low vol factor highly depends on the market risk regime. In a risk rally environment, low vol typically underperforms the market significantly. Figure 70 plots the cumulative IC decay, which shows that low vol is a low turnover factor with slow decay.

Figure 69: Time series of rank IC for low vol factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

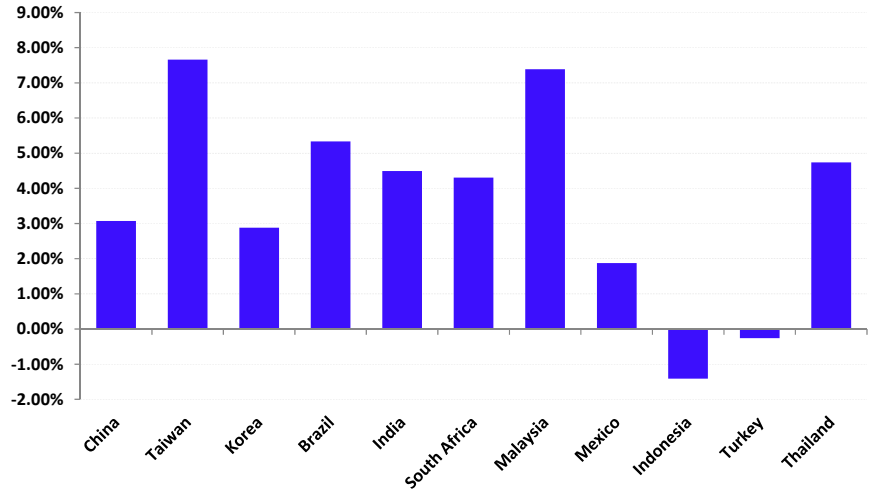
Figure 70: Cumulative IC decay for low vol factor



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 71 shows the average performance of low vol in different GEM countries. We can see that low vol works well for most countries, with the exception of Indonesia and Turkey.

Figure 71: Average rank IC of low vol factor for different countries

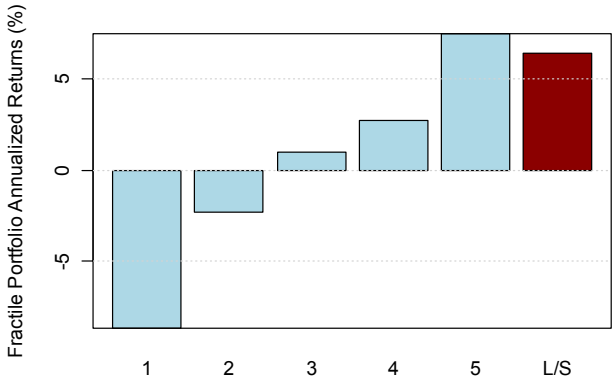


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

A case study of how low vol performs in Taiwan and Indonesia

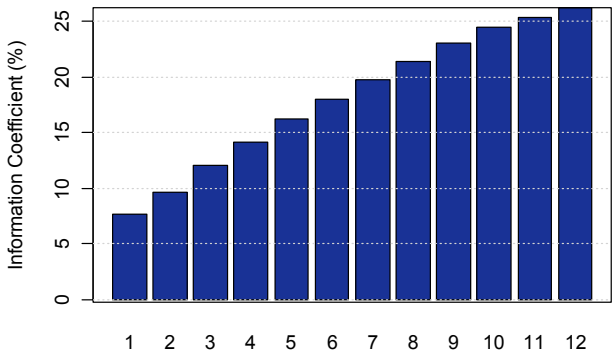
Since low vol performs really well in Taiwain, let's take a deeper dive. Figure 72 shows the returns of the five quintile portfolios in Taiwan, which shows that low vol has a linear monotonic payoff pattern. Figure 75 also confirms that low vol also decays slowly in Taiwan.

Figure 72: Quantile portfolio annualized return for Taiwan



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

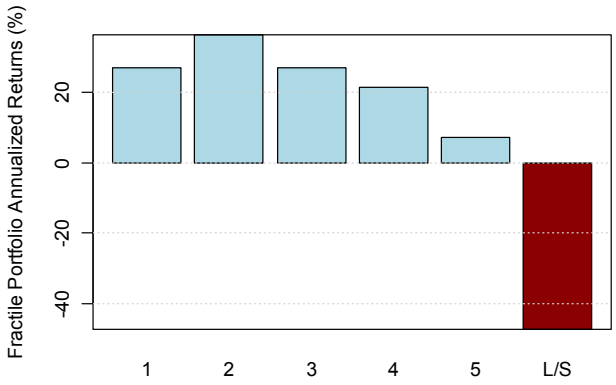
Figure 73: Cumulative IC decay for Taiwan



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

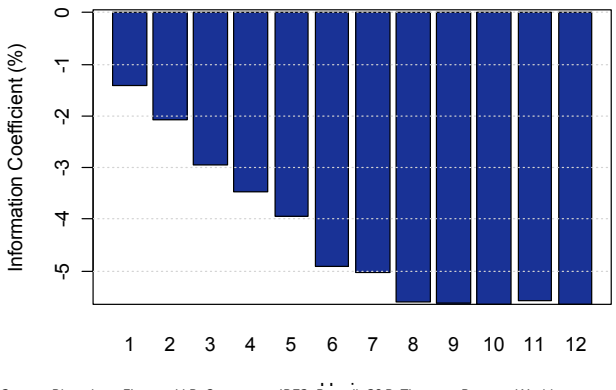
As another extreme, low vol struggles in Indonesia. The direction is almost exactly the opposite, with low vol stocks delivering the lowest returns (see Figure 74). Performance also appears non-linear, with quintile two (second highest volatility) as the best performing quintile. Figure 75 shows the cumulative IC decay for Indonesia. The direction of low vol factor is the opposite of it in other countries, which means in the long run, riskier stocks have indeed delivered higher returns in Indonesia.

Figure 74: Quantile portfolio annualized return for Indonesia



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

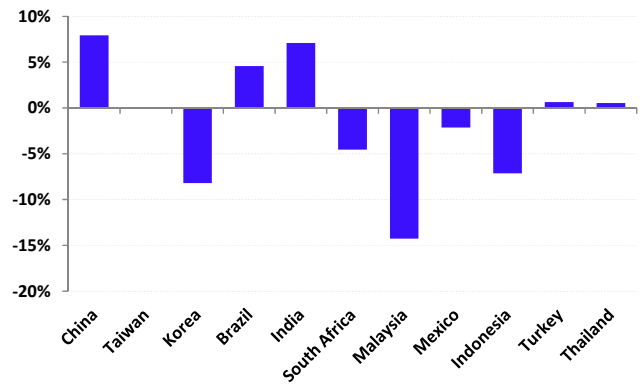
Figure 75: Cumulative IC decay for Indonesia



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

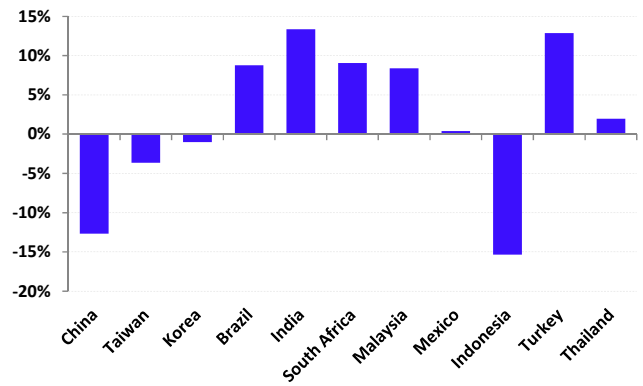
Low vol factor also shows an interesting seasonal pattern. Figure 76 shows the average January rank IC for low vol factor by country. This "January effect" exists for most of countries, where risky stocks outperform in January. However, for East Asian countries like China, Taiwan and Korea, there appears to be a "February effect" (see Figure 77). This might be associated with the Chinese New Year effect, which is usually in February. The so-called January (or February) effect is typically attributable to a behavior bias that investors are optimistic at the beginning of the year and are more likely to buy risky assets.

Figure 76: Average rank IC in January



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 77: Average rank IC in February



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Factor weighting schemes in GEM

In the previous section, we built a simple equally weighted composite factor for each of six style categories. In this section, we use those six composite factors as the building blocks to construct multi-factor stock-selection models. We begin by comparing different factor weighting schemes in GEM. In the end, we want to show how our dynamic Robust Multi-Factor (RMF) model can be an effective alternative to traditional factor weighting algorithms[7].

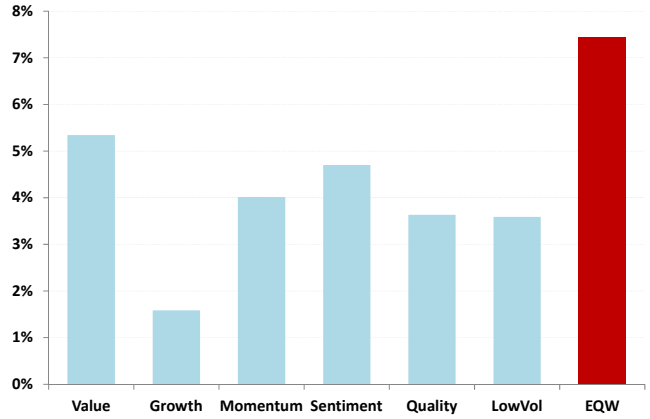
Equal weighted multi-factor model (EQW)

The simplest way to construct a multi-factor model is to equally weight all factors that we want to use. EQW is supposed to be robust to over-fitting and look-ahead bias. Sometimes, it does outperform other more complicated weighting schemes (see DeMiguel, Garlappi, and Uppal [2007]).

Figure 78 and Figure 79 show the average rank IC and risk adjusted rank IC of the equally weighted multi-factor model compared with each individual style factors. The average performance of the EQW model is indeed much better, but the risk adjusted performance is only marginally higher than value and sentiment, due to the relatively high variation of the EQW model (see Figure 80). With an equally weighting scheme, more volatile factors naturally play bigger roles in the final model; and therefore EQW is not necessarily risk neutral. The EQW model also suffered during the global financial crisis (see Figure 81), when most of the underlying factors struggled.

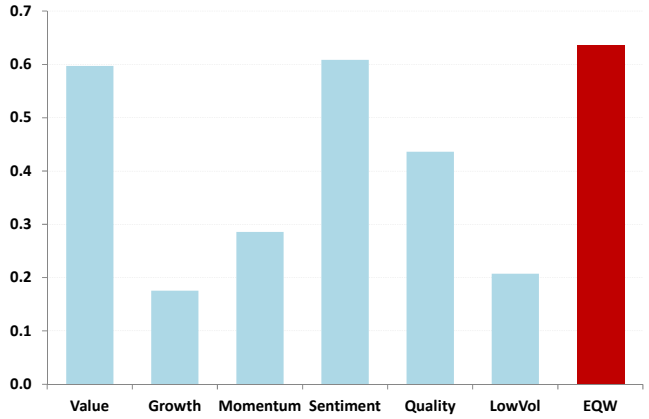
The equally weighted approach would have been more appropriate, if the underlying factors had similar volatilities and expected performance. In addition, the correlation among the six underlying factors also varies significantly (see Figure 82).

Figure 78: Average rank IC for different composite style factors



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

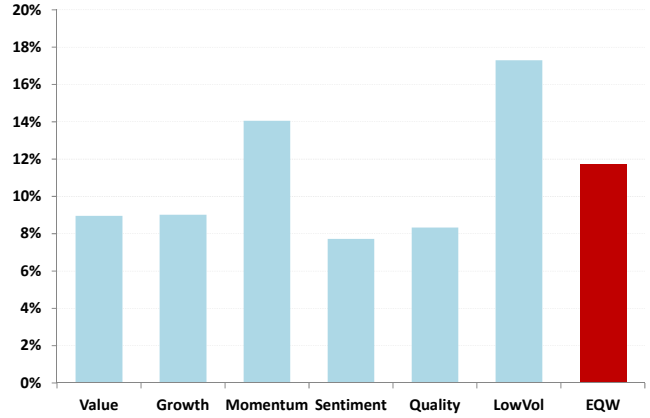
Figure 79: Risk adjusted rank IC for different composite style factors



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

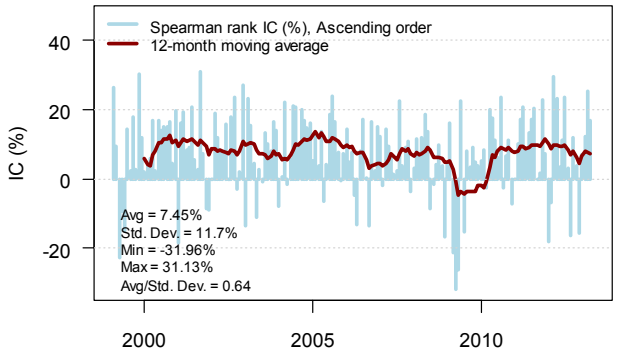
[7] For a more in-depth overview of factor weighting algorithms, please refer to Luo, *et al* [2010b].

Figure 80: Volatility of rank IC for different composite style factors



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 81: Time series of rank IC for the multi-factor using equal weighting



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 82: Correlation matrix

	Value	Growth	Momentum	Sentiment	Quality	LowVol
Value	100%					
Growth	0%	100%				
Momentum	-28%	46%	100%			
Sentiment	-19%	53%	69%	100%		
Quality	43%	41%	37%	26%	100%	
LowVol	16%	-15%	26%	15%	44%	100%

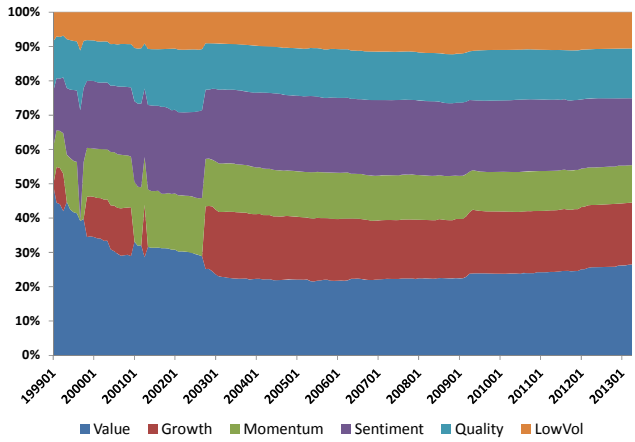
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Risk parity factor weighting model (RP)

One alternative to equally weighting is to weight the underlying factors using a risk parity methodology (Alvarez, *et al* [2011b], Luo, *et al* [2013a] and [2013b]). Recall that in risk parity, we assign equal risk budget to each factor, which tends to overweight less volatile factors. For a given date, we use an expanding window to calculate the covariance matrix of the six underlying factors. The backtesting of the RP model begins after we have one year of data.

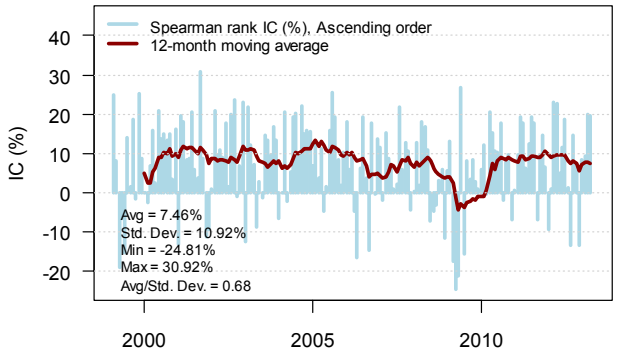
Figure 83 shows factor weights over time under the risk parity weighting methodology. Value and sentiment factors tend to have lower volatilities, which results in higher weights allocating to them. Interestingly, growth, as one of the worst performing factors, actually receives the third highest weight. This is due to the low volatility of the growth factor (see Figure 80), because risk parity does not take the alpha (performance) of the factor into account. Figure 84 shows performance of the RP multi-factor model. This model delivers better performance than the more naïve EQW model.

Figure 83: Dynamic weight for different styles using risk parity weighting



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 84: Time series of rank IC for the multi-factor using risk parity weighting



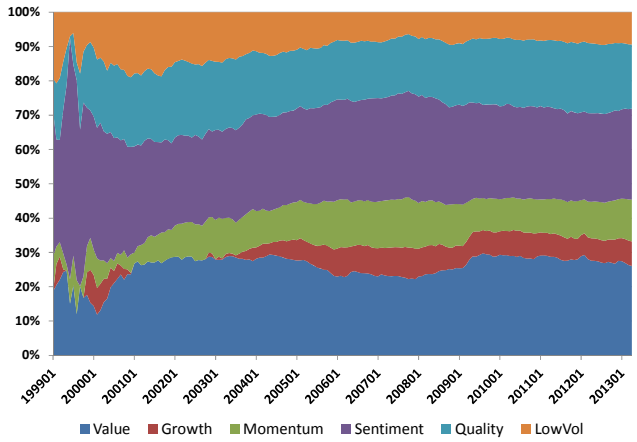
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Alpha-weighted multi-factor model (AW)

EQW and RP models ignore expected factor returns (i.e., alphas) in the factor weighting process. Another alternative is to weight the factors by their performance, i.e., alpha. Basically, we assign higher weights to factors with better expected performance. In addition it is important to take the performance variation into account, therefore, we use the risk adjusted rank IC as the measure of alpha. Similar to risk parity weighting, we use an expanding window to calculate risk adjusted rank IC. If the risk adjusted rank IC at some point is negative, we will assign a zero weight to that factor, because many investors are probably reluctant to bet against a common factor.

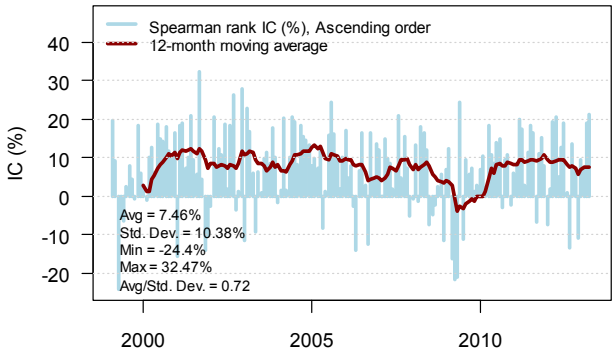
Figure 85 shows the weight of the six factors over time under the AW model. Since value and sentiment have been the best two factors in GEM, we have assigned the highest weights to these factors. On the other hand, growth factor has negligible weight, due to its dismal performance. Figure 86 shows the time series of rank IC of the AW model — it is comparable to an RP model with a slightly lower risk.

Figure 85: Dynamic weight for different styles using alpha weighting



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 86: Time series of rank IC for the multi-factor using alpha weighting



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Grinold & Kahn weighting (GKW)

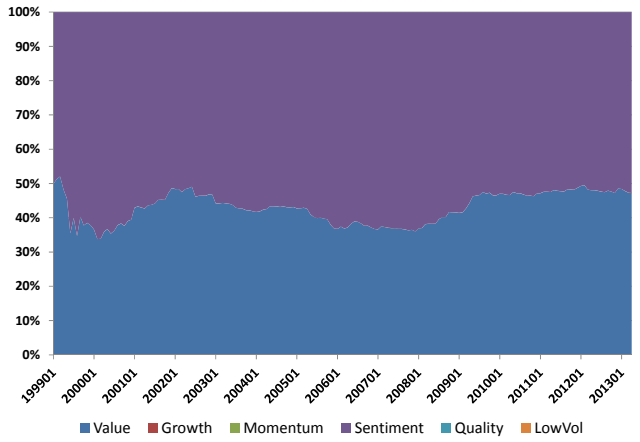
The most traditional and probably also most commonly used factor weighting approach is based on the mean-variance optimization theory (see Grinold and Kahn [1999] or more recently, Qian, Hua, and Sorensen [2007]). This model is sometimes referred to as the Grinold & Kahn signal weighting approach. Similar to how mean-variance optimization is applied in portfolio construction, we can apply the same algorithm in factor weighting. The optimal weights based on GKW can be expressed as:

$$w = (\Sigma_{IC})^{-1} \cdot \overline{IC}$$

where Σ_{IC} is the covariance matrix of the IC's, and $\overline{IC}$ is vector of average rank IC's. Both are calculated on a rolling basis. Similar to AW model, we restrict factor weights to be non-negative.

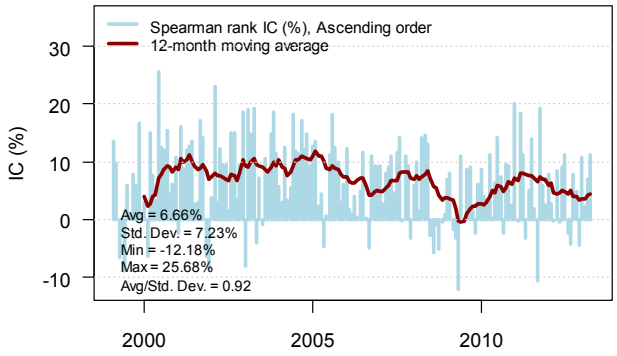
The GKW model essentially becomes a two-factor model, with value and sentiment factors completely dominate (see Figure 87). This is because value and sentiment have the best performance (see Figure 78) and negative correlations with other factors (see Figure 82). The GKW model indeed outperforms the three previous models (see Figure 88), but it's somewhat unrealistic with only two factors in it.

Figure 87: Dynamic weight for different styles using GKW[8]



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 88: Time series of rank IC for the multi-factor using GKW



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

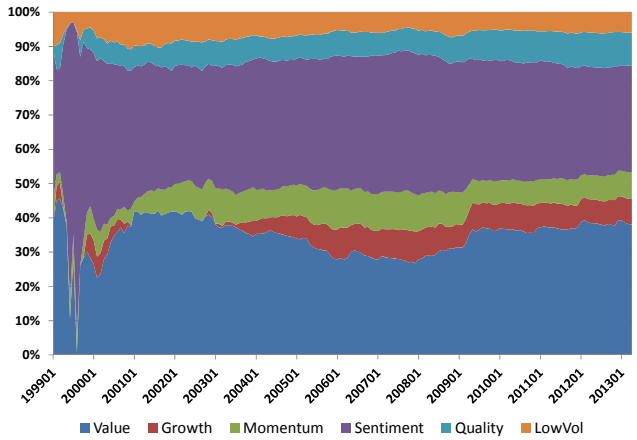
Alpha risk parity factor weighting model (ARP)

So far, we see that EQW, AW, and GKW models all have some issues. RP model does not take factor return into account and may overweight weak factors. AW does not pay enough attention to the volatilities and the correlation structure of the underlying factors. GKW tends to be overly concentrated on few factors. Another interesting alternative is our "alpha risk parity", which makes a nice balance between risk parity and mean-variance optimization (see Alvarez, *et al* [2011] for details).

The main idea of alpha risk parity is to allocate the same amount of risk budget to every unit of alpha. In this scheme, if a factor has better historical performance, lower volatility as well as lower correlation with other factors, it will get a higher weight. Figure 89 shows the weight of each factor under the ARP model. Now value and sentiment factors have significant weights, due to their good performance and low volatility. Growth as a low risk and poor performing factor gets small but non-zero weight. Momentum also has only small weights most of the time, due to its high risk.

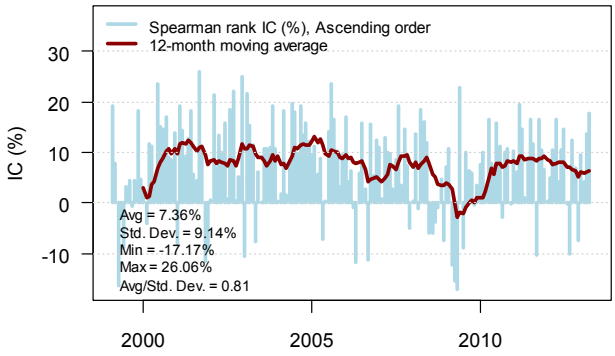
[8] The styles other than value and sentiment have almost zero weight

Figure 89: Dynamic weight for different styles using alpha risk parity weighting



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

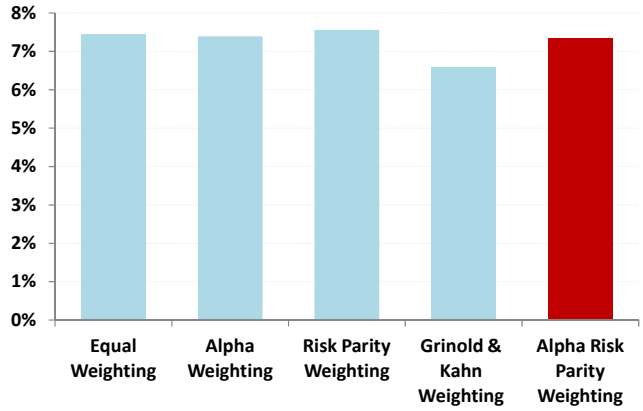
Figure 90: Time series of rank IC for the multi-factor using alpha risk parity weighting



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

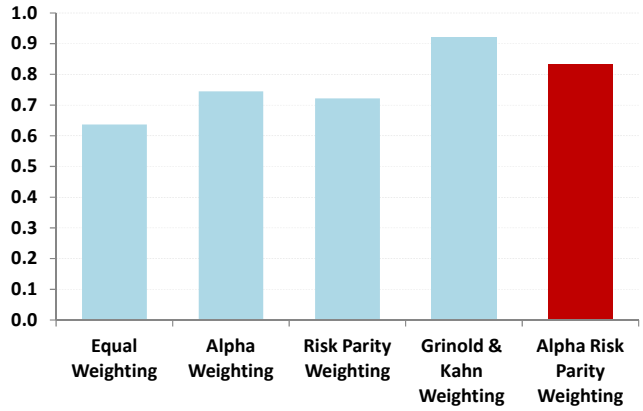
Comparing the five multi-factor models (see Figure 91 and Figure 92), we find that GKW method has the highest risk adjusted performance (but lowest average predictive power). The performance of ARP model is comparable to the GKW model, but it is more balanced and not overly concentrated in few factors.

Figure 91: Average rank IC for different weighting schemes



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 92: Risk adjusted rank IC for different weighting schemes



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Factor normalization and neutralization in GEM

In Wang, *et al* [2012, 2013], we discussed at length of how neutralizing factors within countries and/or sectors can greatly improve a stock-selection model's stability and performance. In this section, we study how to apply similar techniques in GEM.

For the rest of this research, we use the ARP multi-factor model as the main model. As we know, factor values might be vastly different in different countries or sectors. If we rank stocks across different countries or sectors, we might have significant country or sector bias. Therefore, in the rest of this section, we will explore different neutralization techniques that have proven to be useful in Wang, *et al* [2012, 2013].

To neutralize within a category (e.g. countries or sectors), we normalize the factor scores within that category. A multi-factor model is then constructed based on the neutralized factors.

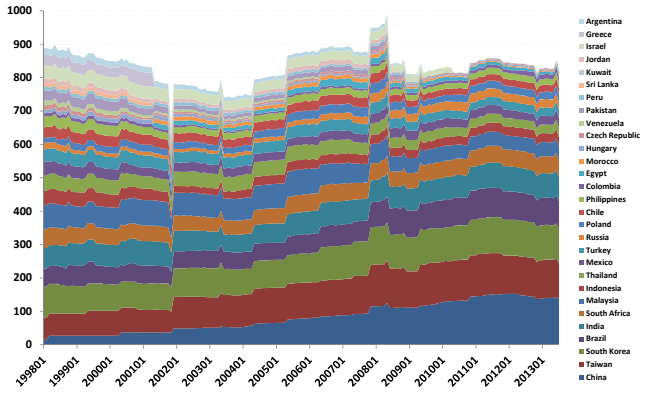
Country neutralization vs. region neutralization

For emerging markets, different countries can be quite heterogeneous; therefore, country effect probably dominates sector effect. Country neutralization is an intuitive starting point. However, our universe covers over 20 countries and many small countries do not have enough coverage.

Figure 93 shows the number of stocks in each GEM countries. More than half of the countries do not have ample coverage. If a country only has a few stocks, then normalizing a factor within that country creates a problem as there is not much cross sectional information we can obtain from only a few stocks.

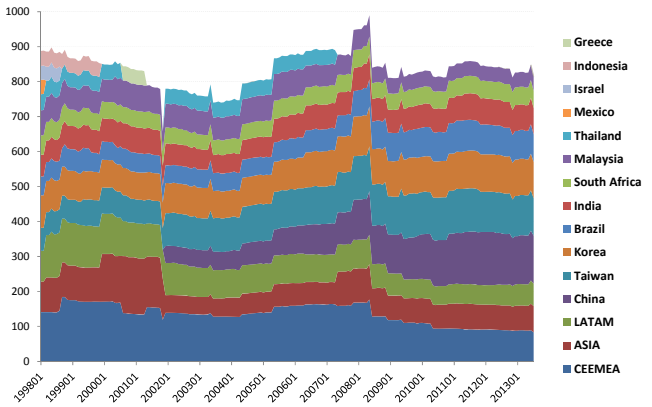
Our remedy is to use region neutralization. We combine the smaller countries into three regions: LATAM, ASIA and CEEMEA. In order to avoid look-ahead bias, we define a "small country" at every point in time — a country with less than 40 stocks. Figure 94 shows the resulting regional coverage. For example, China used to be a "small country" before 2002, therefore it was classified as part of Asia. Today, it's the largest GEM country with the most number of stocks.

Figure 93: # of stocks in each country for MSCI EM



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 94: # of stocks in each region for MSCI EM



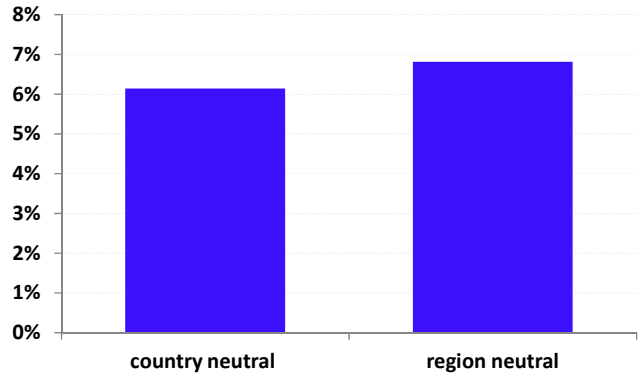
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

We apply the neutralization techniques at the individual factor level. We first neutralize each of the six style factors and then we apply the ARP dynamic weighting algorithm to the six style factors.

Figure 95 and Figure 96 compare the average rank IC and the risk adjusted rank IC for the ARP model using country and regional neutralization techniques, respectively. The regional neutralization technique is clearly better.

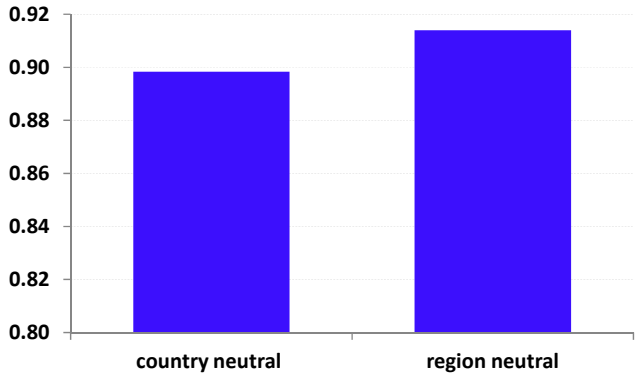
- First, more information is typically lost with a more granular neutralization, but at the same time also achieves a lower risk. Generally speaking, neutralization should decrease the average performance, but improve the risk adjusted rank IC. This is why the country neutralization has lower average rank IC.
- Second, as we have shown in the previous section, factors across countries in the same region usually have similar performance and lower variability, which explains why the risk adjusted rank IC for country neutralization is also lower.

Figure 95: Average rank IC



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 96: Risk adjusted rank IC



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

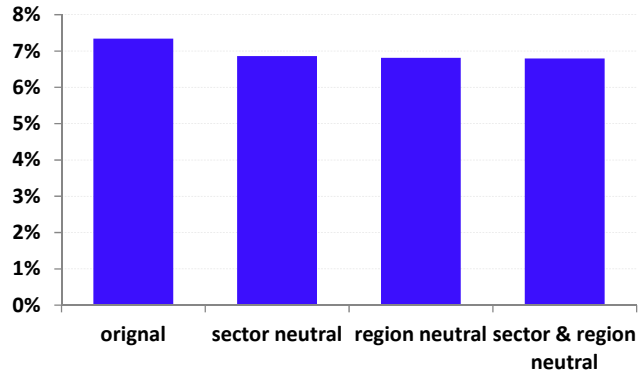
Region + sector neutralization

We can further extend the regional neutralization scheme to incorporate sectors. For example, we can neutralize a factor by each sector in each region. However, many

sectors in small regions do not have enough coverage. Therefore, we use an alternative method to accomplish the region+sector neutralization. We equally weight the sector neutralized and regional neutralized scores for each of the six style factors. Then we use our ARP factor weighting algorithm on these six region+sector neutralized factors.

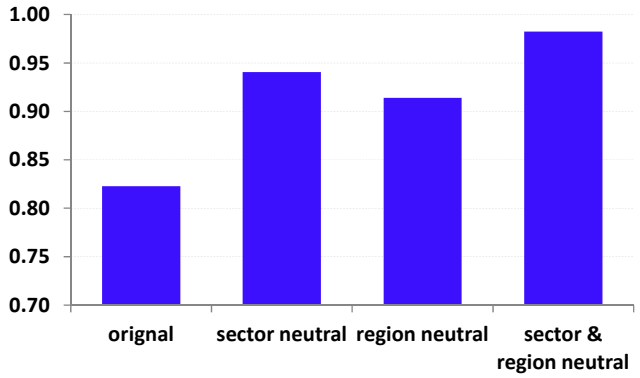
As shown in Figure 97 and Figure 98, although the average performance is comparable, the risk-adjusted IC clearly favors our region+sector neutralization technique. Finally, Figure 99 demonstrates that our region+sector neutralization techniques improve performance for all six underlying factors, as well our over ARP model.

Figure 97: Average rank IC for different neutralization techniques



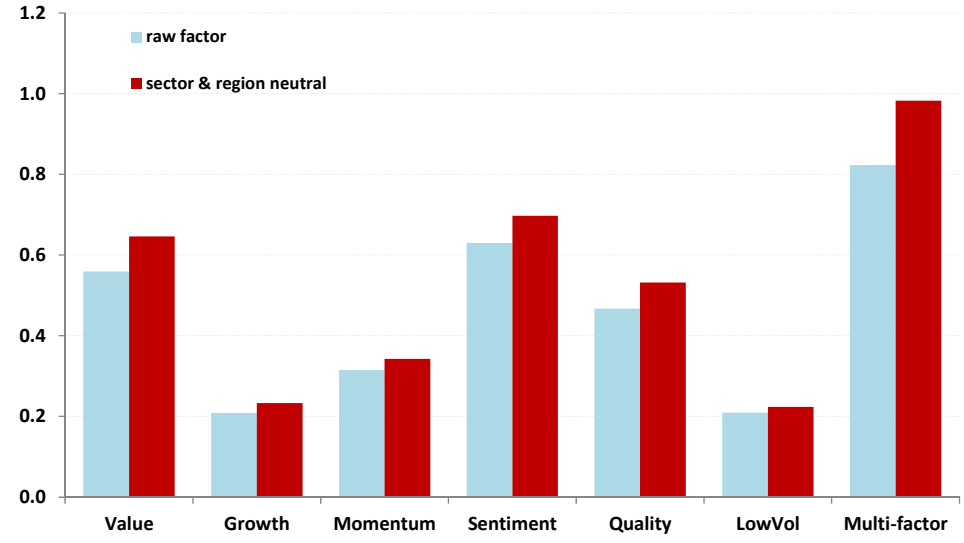
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 98: Risk adjusted rank IC for different neutralization techniques



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 99: Risk adjusted rank IC for different composite style factors with and without neutralization



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Should we neutralize at the model level or leave everything at the portfolio construction stage?

Traditionally, investors control for country/sector biases and exposures at the portfolio construction stage. The most common approach is to set country and/or sector

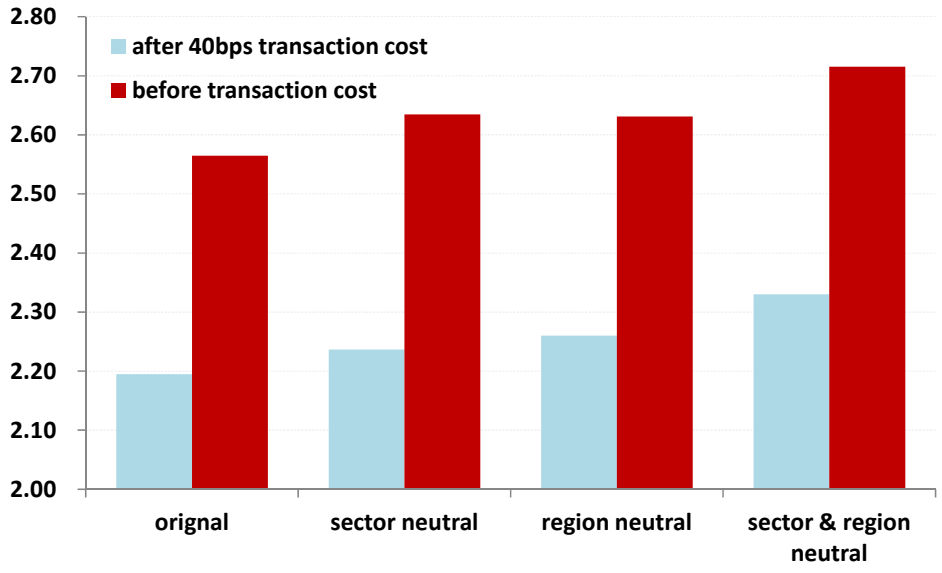
constraints in the optimizer. In this section, we use our ARP model with and without region+sector neutralization and construct portfolios with and without country/sector constraints in the optimizer. The purpose of this exercise is to see whether region/sector neutralization at the signal level is more effective than leaving everything to the portfolio construction stage. We will address more realistic constraints in the next section. Here is the list of constraints for this demonstration:

- 2x leverage, i.e., for $1 capital, the strategy invests in $1 long and $1 short
- Target annualized risk: 4%
- Maximum single stock weight: 1.5%
- Sector neutral (maximum 5% sector exposure)
- Country neutral (maximum 5% country exposure)
- Turnover constraint: 40% (two-away) monthly

Figure 100 compares the Sharpe ratios of our ARP model, with and without transaction cost. To be conservative, we set transaction cost as 40bps per trade. The region+sector neutral ARP model has the highest Sharpe ratio both before and after transaction cost.

In the rest of the paper, we will refer to this region+sector neutralized ARP multi-factor model as the Robust Multi-Factor (RMF) model. We will use this model as the main alpha source when we discuss different realistic constraints for GEM portfolios.

Figure 100: Sharpe ratio of the optimized portfolios for different neutralization techniques before and after transaction



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

GEM portfolio construction

We have shown that factor performance in GEM tends to be stronger than in developed markets. The optimized long short portfolio using our Robust Multi-Factor (RMF) model has a Sharpe ratio of over 2.3x even after 40bps of transaction cost. Is it all that easy to capture alpha in GEM?

In reality, there are many obstacles we need to worry about when investing in emerging markets. Unlike DM, GEM is less liquid, many of GEM stocks are not easy to short, and the market impact of large trades could be significant. These issues are typically ignored in backtesting, but they will affect real-world strategy performance. In this section we will address these issues in more details and provide a more realistic backtesting framework for GEM. We use the RMF model as our alpha throughout this section to be consistent with previous sections. In the next section, we will discuss alternative investment strategies in GEM with other settings.

How much would we lose if we can't short?

One of the main disadvantages when implementing a quant strategy in GEM is that we can't short many stocks. Even if we could, the borrowing cost can be prohibitively high. To demonstrate the impact of shorting on performance, we compare a long/short market neutral strategy with a more realistic strategy that buys GEM stocks and shorts the EM Market[9]. To make sure we make a fair comparison, we set the same constraints for the long/short and the long-only portfolios (see Figure 101).

Figure 101: Constraints for the long-only and long/short portfolio

Long/short portfolio constraints	Long-only portfolio constraints
▪ Long/short market neutral strategy	▪ Long only portfolio against MSCI EM benchmark
▪ 2x leverage, for $1 capital, $1 long and $1 short	▪ No leverage, 100% invested
▪ Target annualized volatility of 4%	▪ Target annualized tracking error of 4%
▪ Maximum single stock weight 1.5%	▪ Maximum single stock weight deviate from benchmark 1.5%
▪ Beta neutral (maximum 5% beta exposure)	▪ Beta neutral (maximum 5% beta exposure relative to the MSCI EM benchmark)
▪ Sector neutral (maximum 5% sector exposure)	▪ Sector neutral (maximum 5% sector exposure relative to the MSCI EM benchmark)
▪ Country neutral (maximum 5% country exposure)	▪ Country neutral (maximum 5% country exposure relative to the MSCI EM benchmark)
▪ Turnover constraint: 40% (two-away) monthly	▪ Turnover constraint: 40% (two-away) monthly
▪ Transaction cost 40 bps one way	▪ Transaction cost 40 bps one way

Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

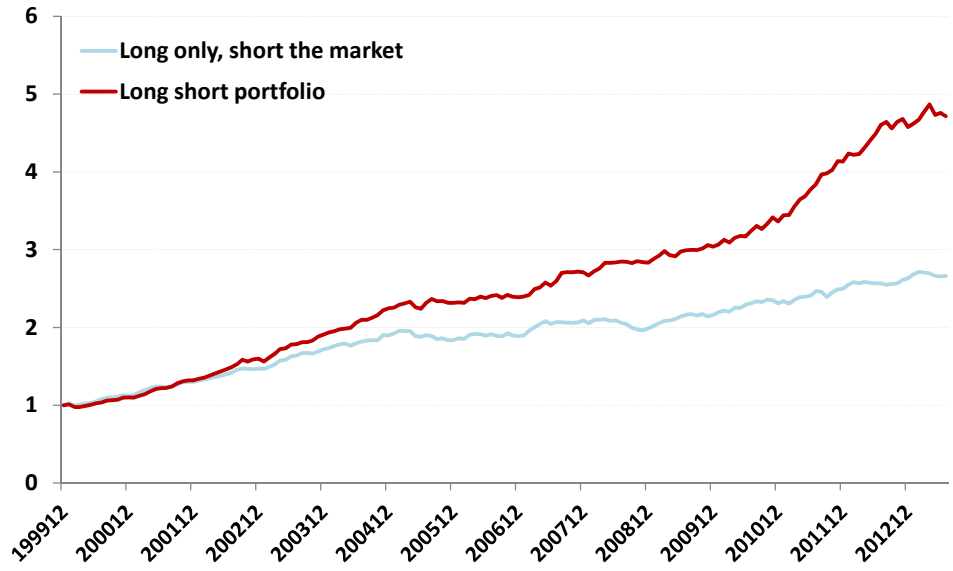
Figure 102 shows the cumulative performance of the two strategies. The long/short portfolio generates almost twice as much return as the long-only/short the market

[9] Shorting the broad EM market is easier than shorting the underlying stocks in the MSCI EM universe. We can short the broad EM market via ETFs or futures.

portfolio. Figure 103 and Figure 104 show the Sharpe ratios and annualized return for the two portfolios. These results show that the long-only constraint is strongly binding and hinders risk-adjusted performance in a significant manner.

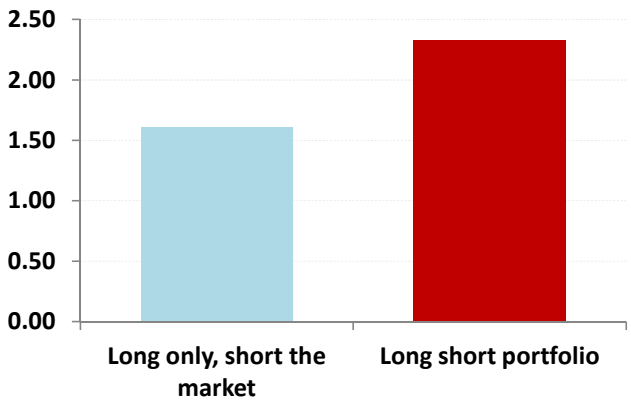
This indicates that a big portion of the alpha in GEM is generated from the short side. The short side typically has smaller and less liquid stocks. In a long-only portfolio, although we can underweight those stocks relative to the benchmark, the amount we can underweight is limited by their weights in the index. Therefore, when optimized against a capitalization weighted benchmark such as MSCI EM, we can't underweight small cap stocks by the same magnitude as their corresponding short in a long/short portfolio. This is the main reason for the gap between these two portfolios. As we know that there is usually more alpha opportunity in small cap stocks; however it is difficult to actually capture this opportunity due to their high trading costs. An experienced prime broker with deep coverage and sufficient stock lending inventory can be of tremendous help in capturing the alpha on the short side. To be conservative, we will focus more on long-only portfolios for the rest of this research.

Figure 102: Long/short vs. long only, short the benchmark for RMF model



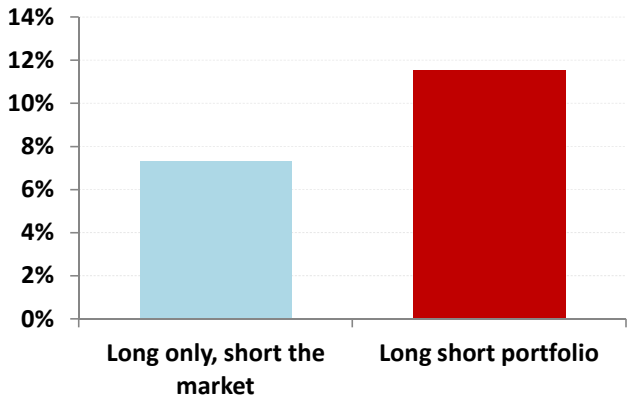
Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 103: Sharpe ratio comparison



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 104: Annual return comparison



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

The liquidity constraint: size matters

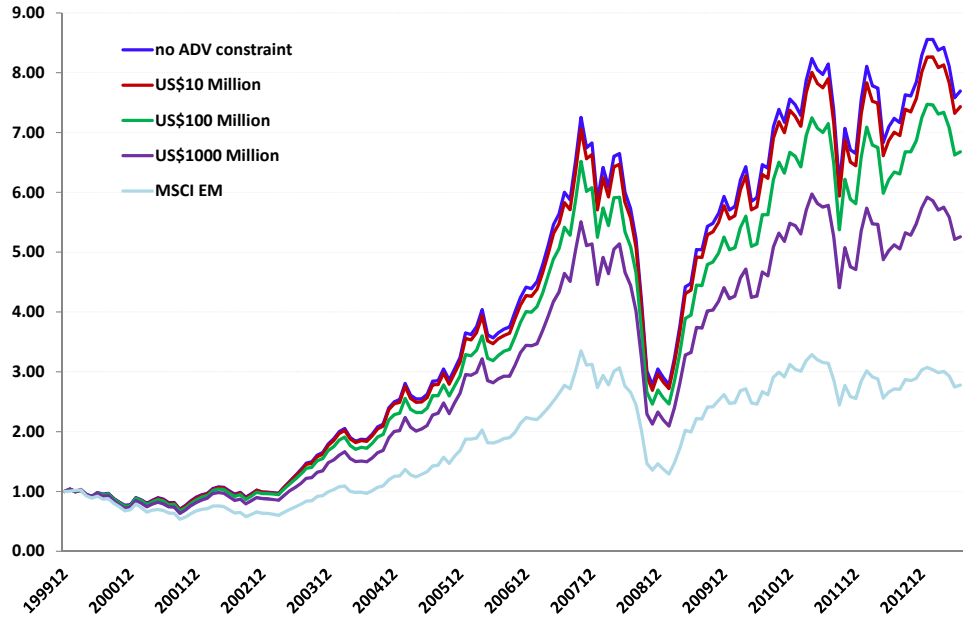
Another central concern when investing in emerging markets is liquidity. Even though MSCI EM includes only investable large- and mid-cap stocks, liquidity can still be an issue for sizeable portfolios. To accommodate liquidity, we can set an ADV (average daily volume) constraint — for example, for each stock we can't trade more than 10% of ADV at the rebalance date. To make a fair comparison, we set all the other constraints to be the same:

- Long only portfolio against the MSCI EM benchmark
- No leverage, 100% invested
- Target annualized tracking error of 4%
- Maximum single stock weight deviate from benchmark: 1.5%
- Beta neutral (maximum 5% beta exposure relative to the benchmark)
- Sector neutral (maximum 5% sector exposure relative to the benchmark)
- Country neutral (maximum 5% country exposure relative to the benchmark)
- Turnover constraint: 40% two way per month
- Transaction cost: 40 bps per trade one way

We optimize the portfolio with and without the ADV constraints. With the ADV constraint, portfolio size matters. We re-base the portfolio size at each rebalance, so that the AUM stays constant. We do this to neutralize the path dependency of the wealth curve so that size impact is not directly dependent on past performance. Otherwise, if a strategy performed well in the past, it would have a larger size impact.

Figure 105 compares the performance of the optimized portfolio with the MSCI EM index. The ideal case with no ADV constraint, as expected, has the best cumulative performance. When the portfolio size is small, e.g., US$10 million, the ADV constraint does not make a big difference. With larger portfolios, the impact on performance is more significant. However, even with US$1 billion, the strategy still outperforms the MSCI EM benchmark.

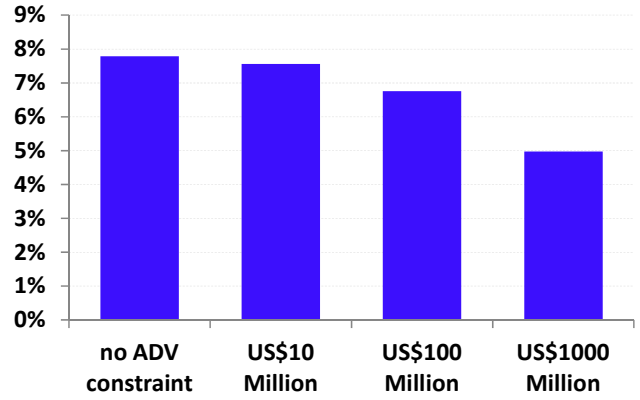
Figure 105: Optimized portfolio with different AUM with ADV constraint



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

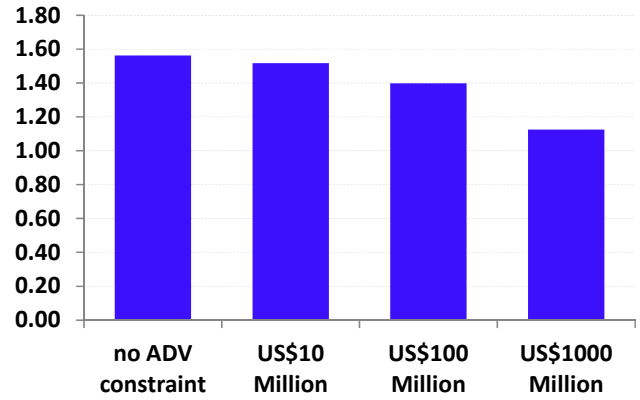
Figure 106 and Figure 107 show the annualized excess return and information ratio for portfolios with different AUM's, compared with MSCI EM benchmark. Strategy performance drops monotonically as size grows.

Figure 106: Annualized access return for optimized portfolios with different AUM



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 107: Information ratio for optimized portfolios with different AUM



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

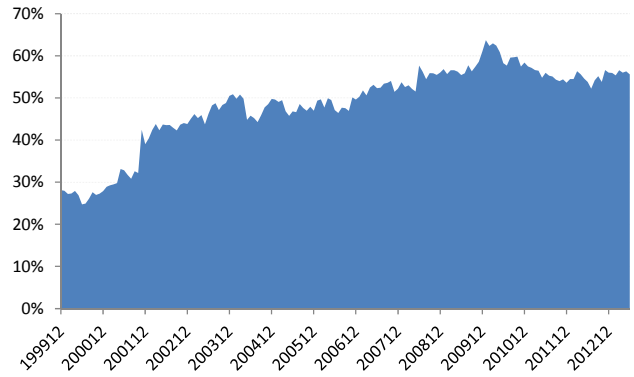
Taking advantage of cross listing

There are many stocks in emerging markets which are also listed on other exchanges. For example many stocks in BRIC (Brazil, Russell, India, and China) countries have American Depositary Receipts (ADRs).

Figure 108 plots the percentage of stocks in the MSCI EM universe that lists in multiple exchanges. If a stock is listed in multiple exchanges, it will be counted multiple times. The percentage of the MSCI EM stocks that are listed on multiple exchanges has been

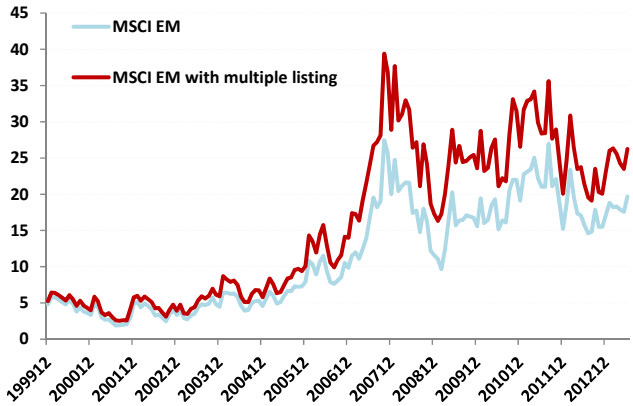
rising over the years. Figure 109 compares the total liquidity (ADV) for MSCI EM with and without stocks listed in multiple exchanges. In early years, the volume we can trade in other exchanges is small, but now there is a huge amount of volume that can be traded via other exchanges.

Figure 108: Percentage of stocks that list in multiple exchanges (stocks list in two exchanges will be count twice)



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 109: Total liquidity (ADV) for MSCI EM with and without the listing in other exchanges (US$ blns)



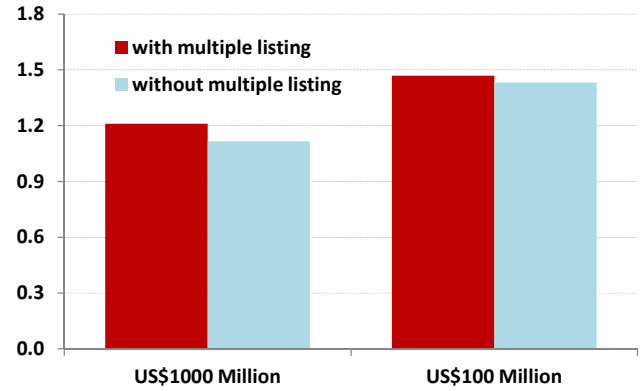
Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Typically, the same stocks traded in different exchanges are highly correlated. Therefore, we can trade the same stocks in other exchanges for better liquidity. We construct portfolios with and without the stocks listed in multiple exchanges, with the same sets of constraints.

As expected, the performance improves if we can invest in the stocks that traded in multiple exchanges (see Figure 110). The larger the size of our portfolio, the more benefit we can get from trading across multiple listings. Figure 111 shows the average number of stocks in the final holdings. Naturally, if we can invest in other exchanges and the larger size of AUM, there are more stocks in the final portfolio.

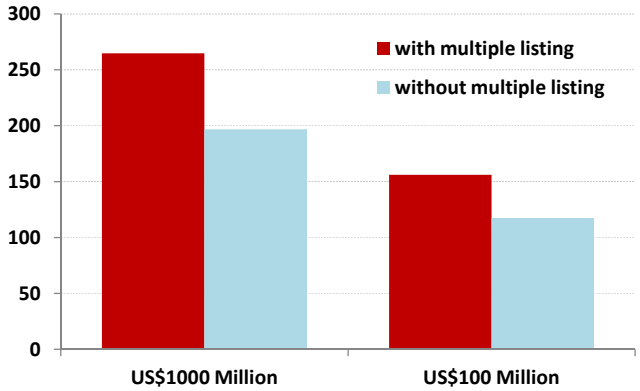
Managing a book with cross listed stocks, however, can be quite challenging from an operational point of view.

Figure 110: Information ratio comparison with and without multiple listing



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 111: Average number of stocks in the holdings with and without multiple listing



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

A realistic transaction cost model for GEM

Up to now, we have assumed a fixed linear transaction cost of 40bps. However, there are problems with fixed transaction cost assumptions. First, as a reminder, total transaction cost includes both fixed cost (e.g., commissions, bid-ask spread, fees, etc.) and variable cost like the market impact. Commission is relatively simple and we typically assume it to be fixed. The market impact cost is more complex and tends to be much bigger than fixed cost. As we know in practice, market impact cost varies depending on the size of the trade and the volatility of the underlying stock — it tends to be higher as we need to trade more shares or if the underlying stock is more volatile.

We use a "Power Law model" to fit the impact cost. It is designed to be as simple as possible, while keeping the accuracy comparable with other well known TCA models. The impact model coefficient I can be written as:

$$\mathrm{I} = \sigma \cdot \gamma \cdot \left(\frac{X}{V}\right)^{\alpha}$$

where: X is the number of shares to trade, V is ADV (shares), σ is a short-term volatility measure, and γ and α are model coefficients. For simplicity, we will use 0.5 for both γ and α. This model applies for trades of size less than10% of ADV, which is the same ADV constraint as shown in all of our optimizations.

For example, if we trade 200,000 shares of a stock with ADV of 20,000,000 shares[10], assuming the daily volatility of 0.015, the market impact cost would be:

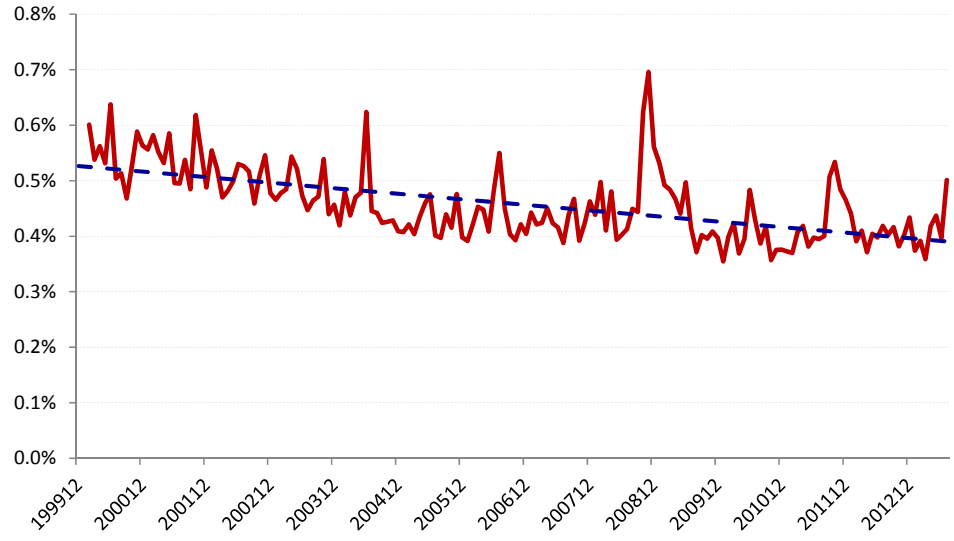
$$\mathrm{I} = \sigma \cdot \gamma \cdot \left(\frac{X}{V}\right)^{\alpha} = 0.015 * 0.5 * (200{,}000 / 20{,}000{,}000)^{0.5} = 0.00075 \text{ or } 7.5bps$$

We set similar constraints as before, with fixed portfolio size of US$100 million. The dynamic transaction cost is calculated by adding up 20bps of fixed cost (commissions, bid-ask spread, fees, etc.) and the market impact model above.

Figure 112 plots the average transaction cost over time. For each stock, the transaction cost is different, since the market impact will be different. The average transaction cost is calculated by total transaction cost divided by the total dollar amount traded. As the GEM market becomes more liquid over time, the average transaction cost has gone down. In addition, during the financial crisis, when liquidity dried up and market was more volatile, there was a big spike in average transaction cost. This model is more realistic compared with the fixed cost assumption.

[10] This would be a very liquid stock

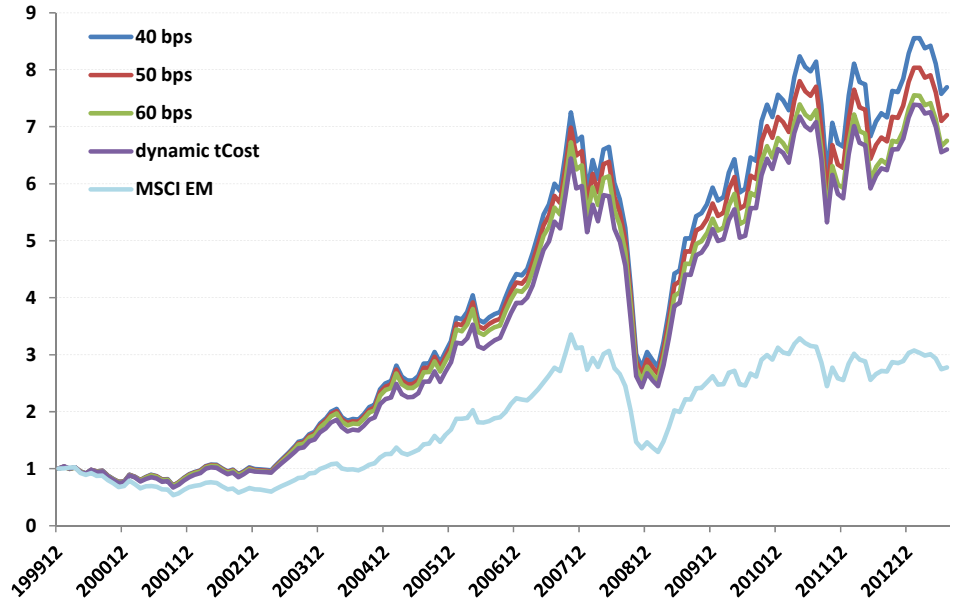
Figure 112: Average transaction cost using dynamic transaction cost with impact model



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

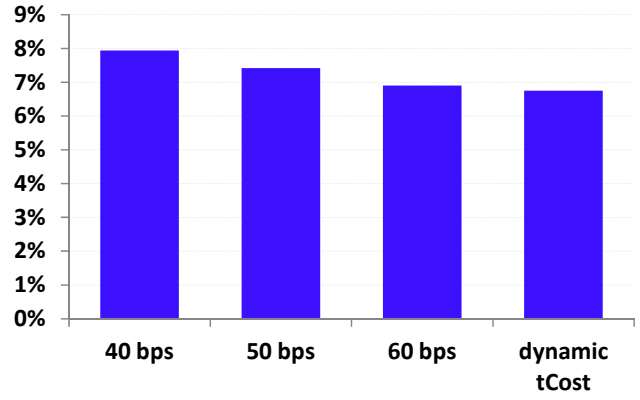
Lastly, we compare the performance of our strategy with our dynamic TCA model with various fixed transaction cost assumptions. The portfolio size is fixed at US$100 million at each rebalance to remove the path dependency issue. The average transaction cost for the dynamic TCA is about 46 bps (see Figure 112) over the backtesting period. However, as shown in Figure 113 to Figure 115, the performance under the dynamic transaction cost model is comparable to a portfolio with 60 bps of fixed cost. This is because during the financial crisis, trading costs were much higher (liquidity dried up and market volatility went up). This once again highlights that simple linear T-cost models tend to be overly optimistic.

Figure 113: Wealth curve for long only optimized MSCI EM portfolio with different transaction cost model



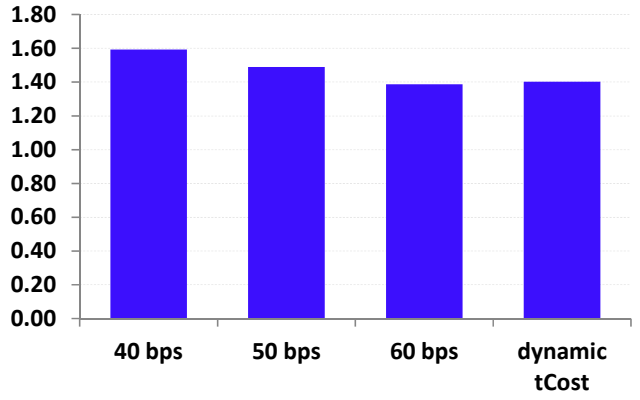
Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 114: Annualized access return for different transaction cost model



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 115: Information ratio for different transaction cost model



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

GEM investment strategies

In the previous section, we focused on one particular investable strategy in GEM – an active/enhanced indexing strategy using our RMF model. In this section, we will study on a few more real-life investable strategies in GEM, ranging from risk-based strategies, active, to absolute return strategies. In addition to the RMF model introduced in this research, we also apply our N-LASR global stock selection model based on machine learning techniques (see Wang, *et al* [2012, 2013]). We will use the dynamic TCA model introduced in the previous section throughout the rest of this research.

Minimum variance strategy

Minimum variance (MinVar) strategy (see Alvarez, *et al* [2011a] and Luo, *et al* [2013a]) is becoming a popular strategy in GEM. The definition for MinVar is quite straight forward — by minimizing the expected risk (variance). MinVar is a risk-based strategy that does not require alpha or return prediction. In Luo, *et al* [2013a], we have shown that MinVar significantly outperforms capitalization-weighted benchmarks in multi-asset, alternative betas, bonds, commodities, sector and country indices, as well as stock portfolios in the US, Europe, Asia ex Japan, Japan, and EM. In this paper we will focus on GEM MinVar, with realistic constraints and transaction costs.

One of the main concerns investing in GEM is the potential volatility in this particular market segment. A low risk strategy like MinVar applied to emerging markets can be an interesting option that gives investors the best of both worlds — participating to a fast growing market and at the same time, focusing on the least risky stocks within this market.

We construct our GEM MinVar portfolio with the following constraints:

- Long only portfolio with no leverage, 100% invested
- Objective is to minimize the portfolio expected variance
- Maximum single stock weight is 10%
- For each stock we can't trade more than 10% of ADV at rebalance
- Dynamic transaction cost
  - 20 bps fix cost (i.e, commissions, bid-ask spread, fees, etc.)
  - Dynamic market impact cost model as described in the precious section
- Initial portfolio size US$100 million

The GEM MinVar portfolio has a Sharpe ratio of almost 1.2x — more than triple the MSCI EM index. It has lower risk and higher return compared to the market index. However, during bull markets and especially in risk rally phases, MinVar tends to underperform the market. Therefore, the active return (MinVar return minus the market) of MinVar is highly negatively (-86%) correlated with the market. MinVar is an ideal index tracking product[11], since the tracking error tends to be high.

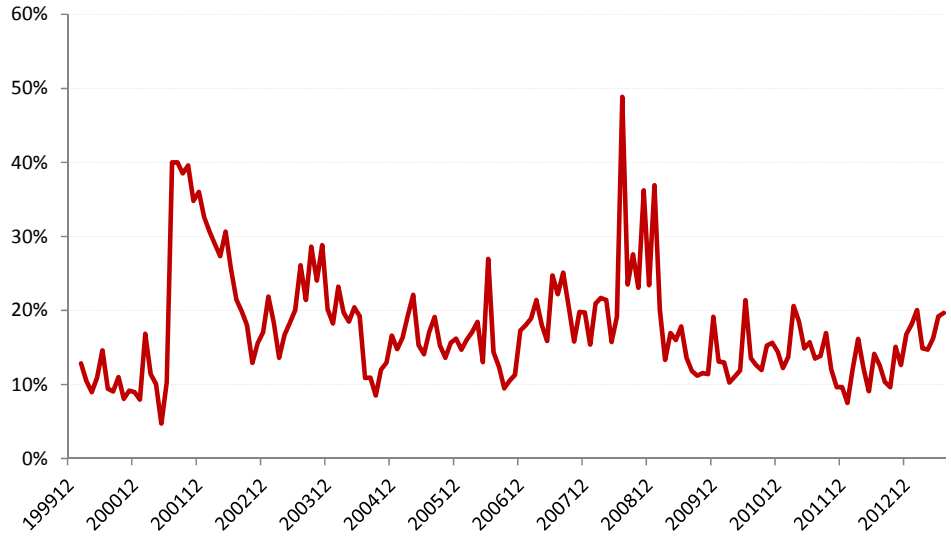
[11] There is not yet a consensus benchmark for low risk types of investment products in the investment community.

Low turnover

In the first iteration, we did not set a turnover constraint in the optimizer in order to assess the natural turnover of the strategy. Intuitively, the turnover for the MinVar portfolio is quite low (see Figure 116) — below 20% most of the time.

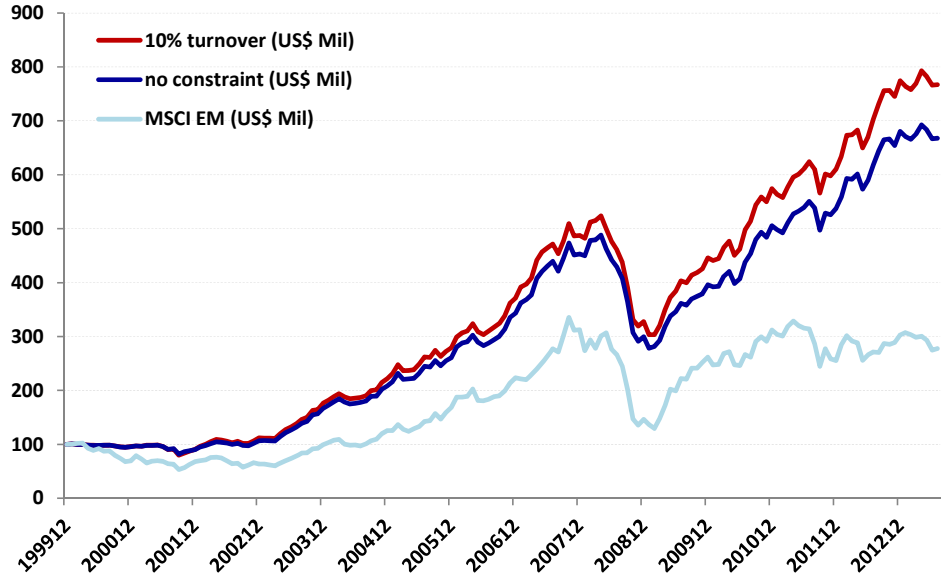
If we set the turnover constraint to be 10% (two-way, per month), the performance is even better (see Figure 117). This is something we have found repeatedly in our past research and is most likely due to noise reduction in the covariance matrix. This illustrates that the MinVar strategy has the appealing property of low turnover. In a stable environment, risk and correlation structure are also likely to be slow moving. In addition, by construction, low volatility stocks usually are large cap stocks, so market impact costs are generally lower.

Figure 116: Two-way turnover of minimum variance (MinVar) strategy in GEM



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 117: Performance of the minimum variance (MinVar) strategy in GEM with different turnover



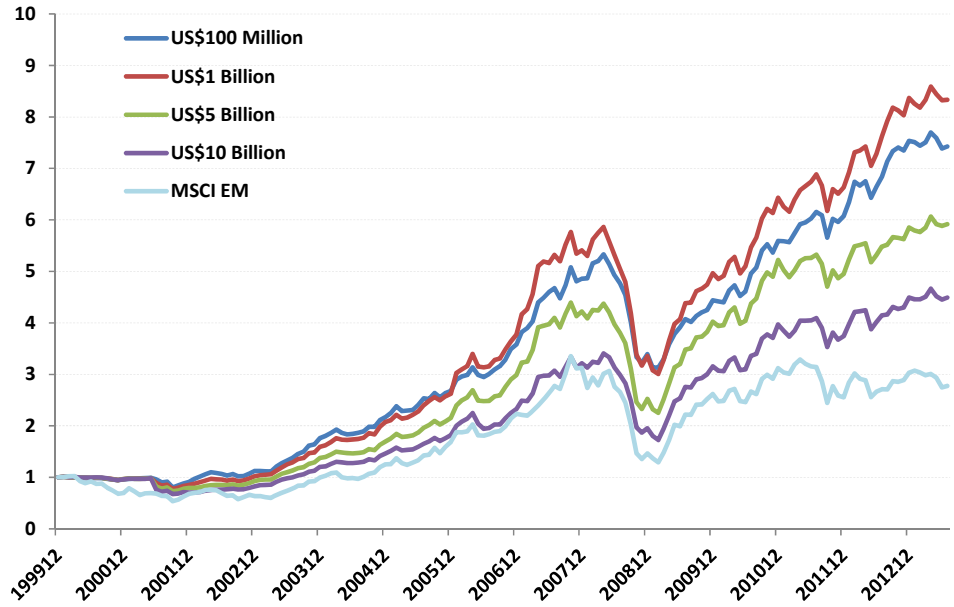
Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

High capacity

Now, let's look at capacity. Figure 118 shows the cumulative performance of GEM MinVar with various AUM levels[12] (from US$100 million to US$10 billion). Figure 119 compares the Sharpe ratios with different AUM levels. Even with a large portfolio of US$10 billion, GEM MinVar strategy still delivers twice higher Sharpe ratio than the broad market. The realized volatility increases as the size of portfolio grows (see Figure 120), but remains significantly below the market.

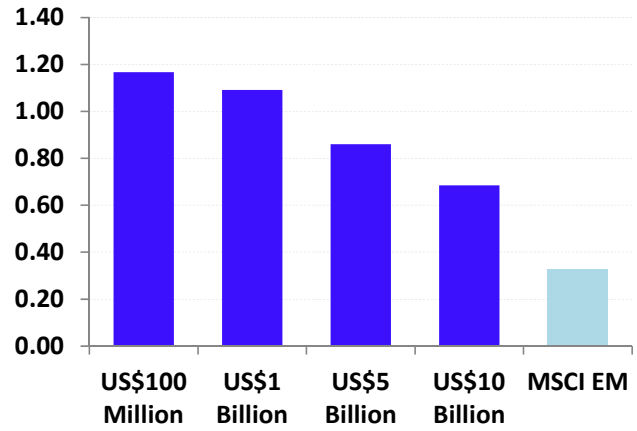
[12] Again, to avoid path dependency, we keep the portfolio size fixed at each rebalance.

Figure 118: Performance of the minimum variance (MinVar) strategy in GEM with different portfolio AUM



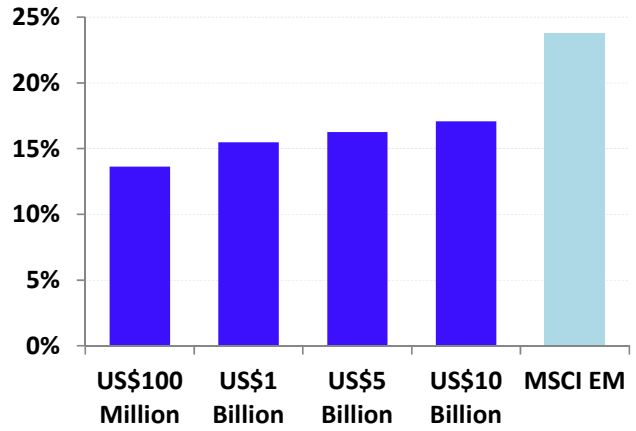
Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 119: Sharpe ratio for different portfolio AUM



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 120: Realized annualized volatility for different portfolio AUM



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Absolute return strategy without an explicit benchmark

The GEM MinVar strategy we discussed earlier does not require return prediction/alpha. Can we improve the performance if we have some alpha signals? In this section, we use our RMF model predicted alpha as the raw ingredient to build a long-only active strategy without referencing to an explicit benchmark, by focusing on absolute returns. We construct our portfolio using a classic mean-variance optimization:

$$\alpha \cdot w - \lambda w' \Sigma w$$

where α is the alpha signal, w is the weight of the portfolio (to be solved by the optimizer), Σ is the covariance matrix[13] and λ is the risk aversion parameter.

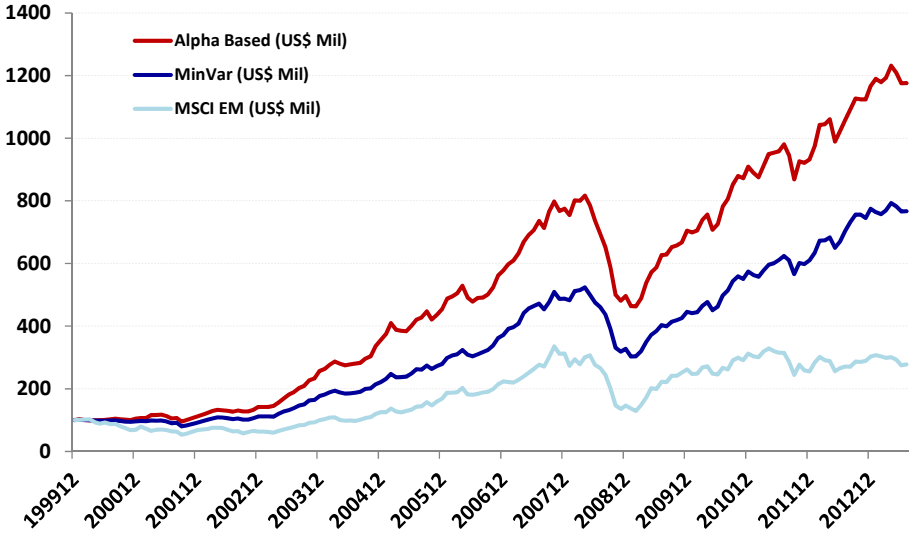
The risk aversion parameter λ is typically calibrated to a specific risk target that the manager is comfortable with. When λ is very large, the portfolio constructed behaves more like a minimum variance strategy, as risk plays a dominate role. When λ is small, the risk term play a smaller role and the realized risk is typically high. We need to find a balance between risk and alpha. If the alpha has strong predictive power we can set smaller λ, otherwise we can set it to be large. It is also related to the scale of alpha.

We set the λ to target an annual volatility of approximately 14%-15%, in line with the risk of the GEM MinVar strategy. Specifically, we construct our active strategy as:

- Long only portfolio with no leverage, 100% invested
- Objective is to maximize risk-adjusted absolute return $\alpha \cdot w - \lambda w' \Sigma w$
- Maximum single stock weight of 10%
- Target turnover: 10% two-way per month
- For each stock we can't trade more than 10% ADV at rebalance
- Dynamic transaction cost
  - 20 bps fix cost (i.e, commissions, bid-ask spread, fees, etc.)
  - Dynamic market impact model described in the precious section
- Initial portfolio size of US$100 million

The long-only absolute return portfolio outperforms the GEM MinVar portfolio (see Figure 121) The Sharpe ratio for the alpha based mean-variance portfolio is over 1.4x (see Figure 122), with an annualized return of 20% (see Figure 123) over the past 13 years. Starting from US$100 million in 2000, the portfolio grows to over US$1 billion in the end.

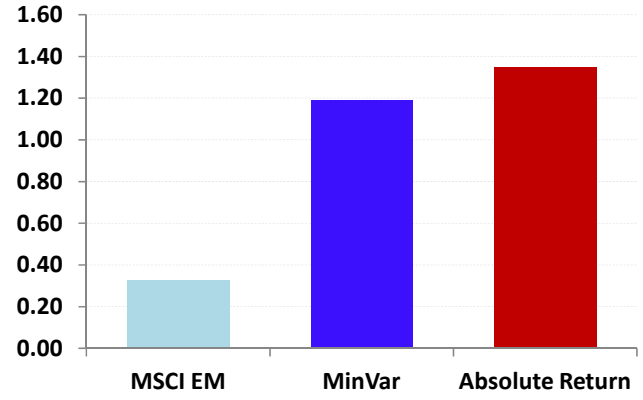
Figure 121: Wealth curve of alpha based strategy compared with minimum variance (MinVar) and MSCI EM benchmark



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

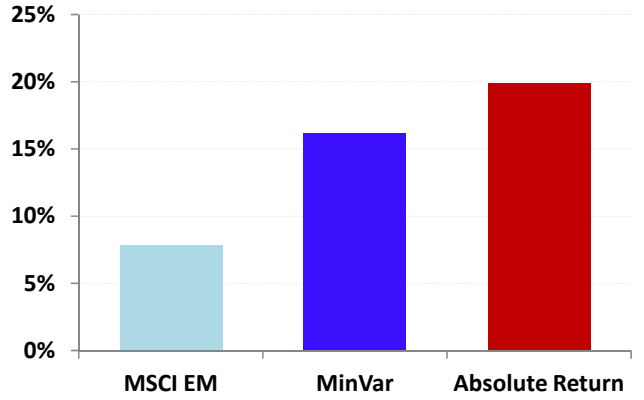
[13] We use Axioma's medium horizon fundamental risk model for emerging markets.

Figure 122: Sharpe ratio



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 123: Annualized returns



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

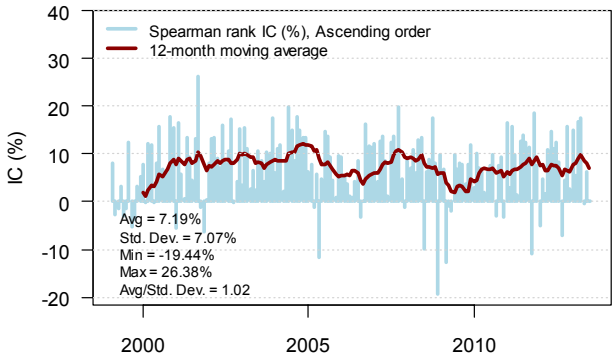
Active enhanced indexing strategy using our N-LASR model

In addition to the RFM model specifically designed for GEM, we also have a global stock selection model called N-LASR (see Wang, *et al* [2012, 2013]). The N-LASR model is built on a machine learning algorithm called AdaBoost. It has shown great live performance and proven to be uncorrelated with traditional linear multi-factor models. In this section, we would like to develop an active enhanced indexing strategy using the N-LASR model. The strategy is otherwise similar to the enhanced strategy constructed using RFM model described in the previous section.

The N-LASR model has better predictive power of future stock returns than the RMF model (see Figure 124 and Figure 125). The performance of the N-LASR model is especially stronger in recently years, as its adaptive nature adds more alpha in a fast changing environment.

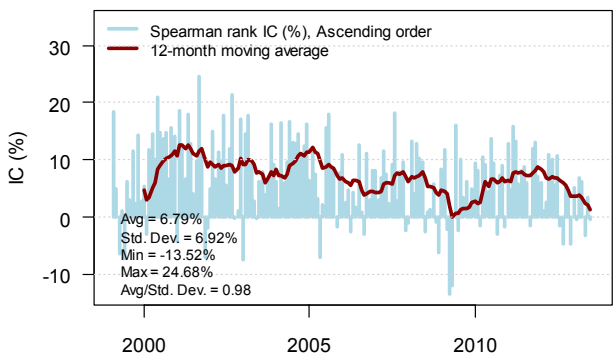
The serial correlation for the N-LASR model is lower than the RMF model (see Figure 126 and Figure 127), which suggests that the turnover of the N-LASR model is likely to be higher. The N-LASR model is dynamically fitted per month, therefore, we naturally expect it to have higher turnover.

Figure 124: Time series of rank IC for N-LASR model



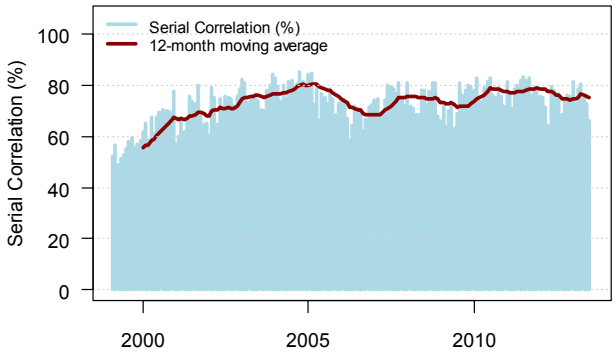
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 125: Time series of rank IC for RMF model



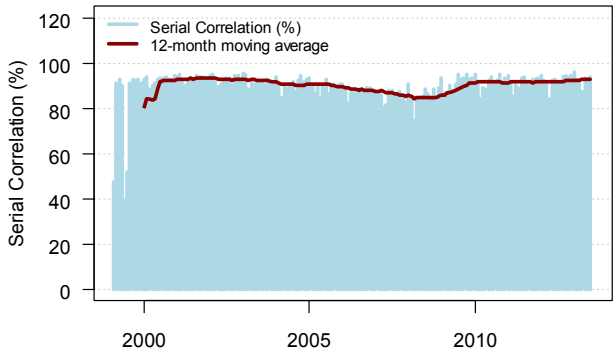
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 126: Serial correlation for N-LASR model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 127: Serial correlation for RMF model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

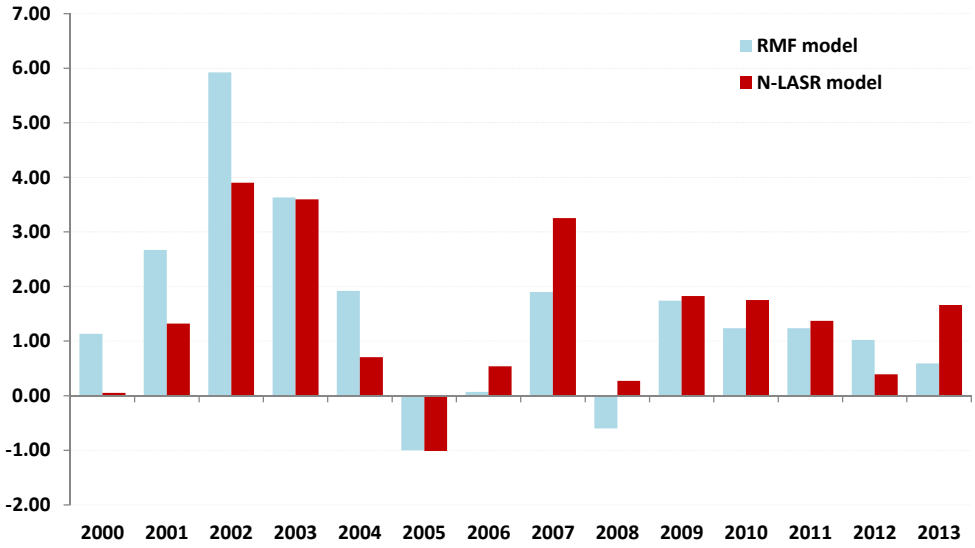
The active enhanced strategy using the N-LASR model is constructed as follows:

- Long only portfolio against MSCI EM benchmark
- No leverage, 100% invested
- Target annualized tracking error of 4%
- Maximum single stock weight deviate from benchmark of 1.5%
- Beta neutral (maximum 5% beta exposure relative to the benchmark)
- Sector neutral (maximum 5% sector exposure relative to the benchmark)
- Country neutral (maximum 5% country exposure relative to the benchmark)
- Turnover constraint 40% two-way per month
- ADV constraint: for each stock we can't trade more than 10% ADV
- Dynamic transaction cost
  - 20 bps fix cost
  - Dynamic market impact cost model as described in the previous section

- Initial portfolio size US$100 million

Figure 128 shows the annualized information ratio of the two models (N-LASR and RFM) by year. Both models have done well over the past 13 years. The N-LASR model only underperformed the benchmark in 2005, while the RMF underperformed in 2005 and 2008. The RMF model performs better in early years, while N-LASR model took over in recent years. After 2006, the N-LASR model beat the RFM almost every single month, despite its high turnover.

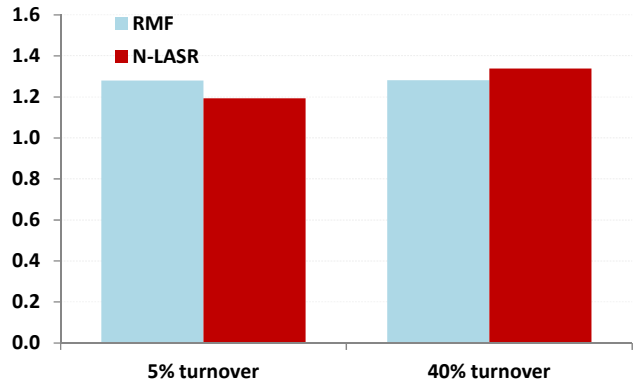
Figure 128: Annualized information ratio by year for optimized portfolio based on N-LASR and RMF models



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

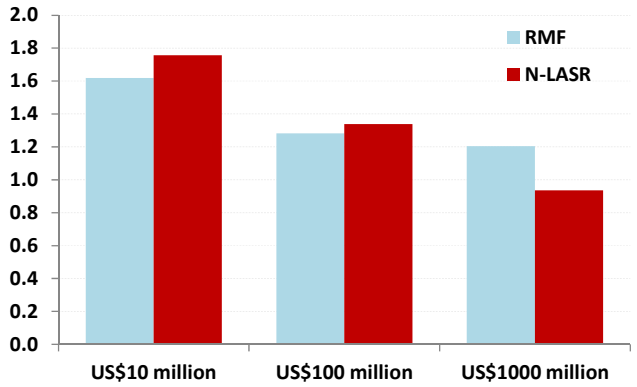
The N-LASR model has lower signal autocorrelation than the RMF model (see Figure 126 and Figure 127); therefore the better performance comes with higher turnovers. Naturally, if we have a tight turnover constraint (e.g., 5% two-way per month), we may not be able to capture the full potential of the N-LASR model (see Figure 129). In addition, large portfolio size also favors the RMF model (see Figure 130). For larger portfolios or lower turnovers, the slow decay RMF is probably a better choice, while for nimble managers, the N-LASR model is a clear winner.

Figure 129: Information ratio for different turnover



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 130: Information ratio for different portfolio AUM

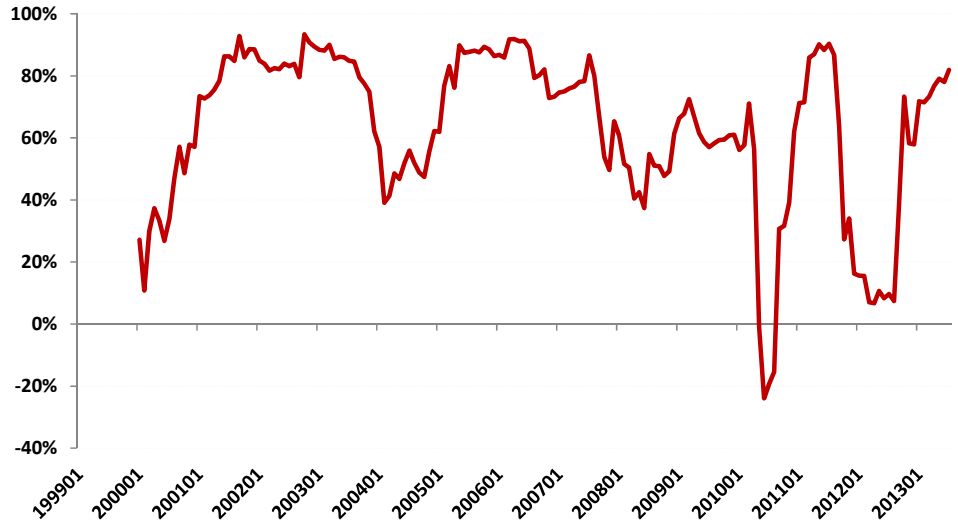


Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

A combined enhanced strategy

Although both the N-LASR and RMF models have strong predictive power of future stock returns, they are not always highly correlated (see Figure 131), which suggests potential diversification benefit by combining these two models together.

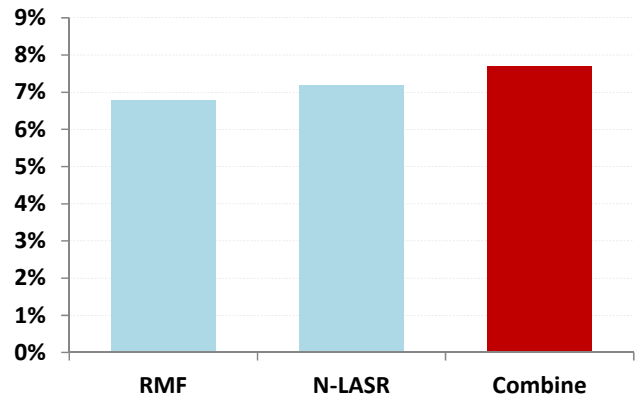
Figure 131: Rolling 12 month correlation of rank IC between N-LASR and RMF model



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

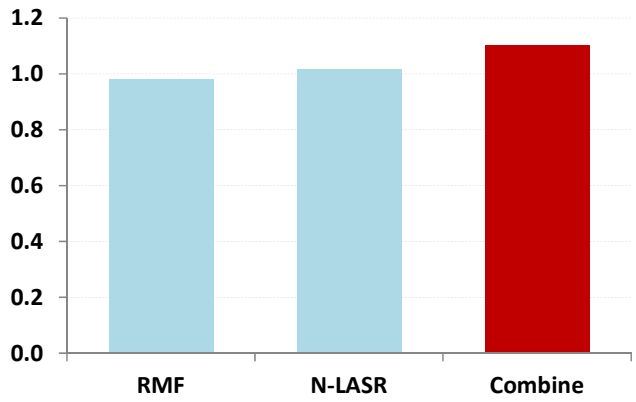
For simplicity, we equally weight the two models and call it the "Combined" model. The combined model has higher average rank IC (Figure 132) and higher risk adjusted rank IC (Figure 133).

Figure 132: Average rank IC



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

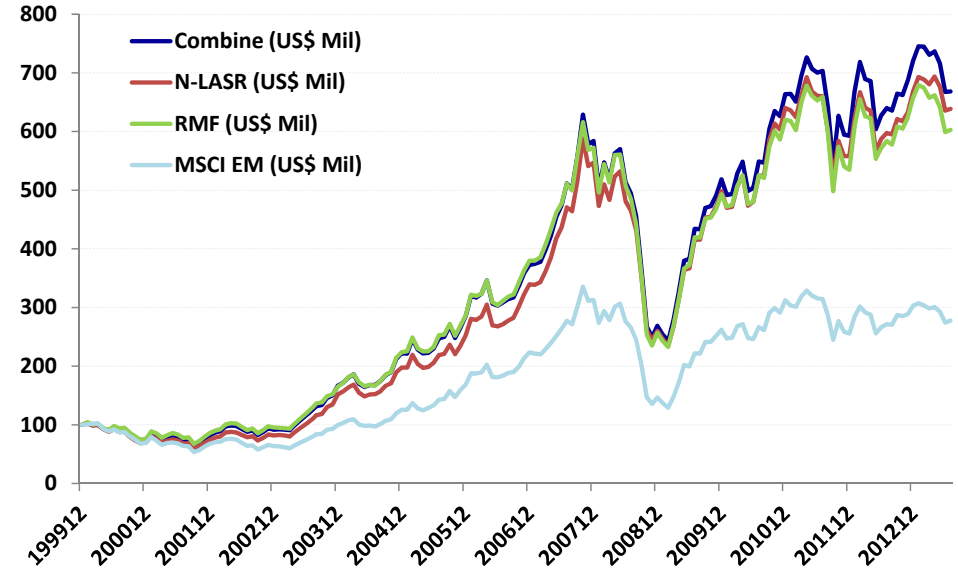
Figure 133: Risk adjusted rank IC



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

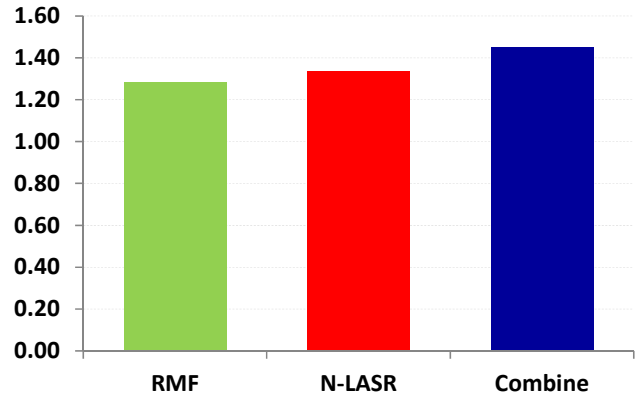
Then we construct a final enhanced indexing strategy using this combined model, with the same setup as the enhanced strategies using the N-LASR and RMF models. As expected, all three enhanced strategies have outperformed the benchmark considerably (see Figure 134 to Figure 136). The combined strategy generates an IR of over 1.4x.

Figure 134: Wealth curve for different strategies



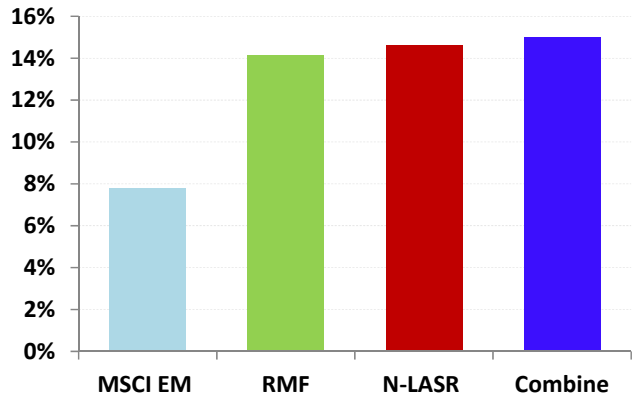
Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 135: Information ratio for different strategies



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 136: Annualized return for different strategies



Source: Axioma, Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

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Appendix 1

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