“In a world increasingly dominated by software and ESG do lower equity valuations result in higher future returns?”

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Abstract—Academcis and market practitioners spend considerable time debating valuation levels, regularly using multiples such as P/E as short-hand. Empirical tests of EMH theory since the 1970’s have highlighed challenges, most notably a ‘value anomaly’, where on average, lower P/E stocks offer higher than expected returns. Taking a multi-country approach, this paper uses public equity market valuation data from the Bloomberg covering 2009 to end 2021, to identify country winners and losers post GFC. It seeks to answer whether lower starting point equity valuations, using EV/Sales and P/E multiples, have had signal power for higher future returns. The importance of the tech sector and growth in ESG investing assets are briefly investigated as alternative explanatory variables of returns. Visualisation techniques and computational methods have been used extensively.

1 Problem Statement

Modern finance theory is underpinned by the Capital Asset Pricing Model and Efficient Market Hypothesis (EMH) [1][2]. In its weak form, EMH states that historical price movements (e.g. charts), volume and historical financials (e.g. 10-Q reports) can’t be used to predict future price direction.

Fama and French have noted that empirical tests of the EMH show anomalies around beta (relative volatility), size and valuation [1]. In particular, stocks with lower valuations have tended to outperform theoretical predictions.

The rise of the digital economy and platform based business models benefiting from positive network effects has largely been ignored to date. As has the emerging influence of Environmental, Social & Governance (ESG) considerations.

Using Bloomberg stock market data, this report visualizes the absolute and relative performance of a range of stock market indices, as opposed to individual companies, in both developed (US, Europe, UK and Japan) and developing markets (Brazil, Russia, India and China) post the Global Financial Crisis (GFC). The signal power of starting point valuation multiples of these indices to future short-term Total Shareholder Returns (TSR) is evaluated graphically.

In addition, the role of commercial innovation is visually considered as a driver of returns. This study identifies every public company founded since 1975 that has achieved a market capitalization >US$100bn by end-2021 (“mega-caps”), grouped by origin and sector. The potential predictive power of ESG investing to returns is also briefly examined.

2 State of the Art

As long ago as 1688, Josef de la Vega observed:

“As there are so many people who cannot wait to follow the prevailing trend of opinion, I am not surprised that a small group becomes an army.”

Put another way, in one of the first books written on markets, De la Vega perceived that share prices on the Dutch exchange were driven by the communication and proliferation of opinions. Given the prospect of dreamy profit, significant academic and investor interest is shown in the signal power of valuation analysis on future price performance.

In an empirical study, covering 189 companies, over 25 years, Nicholson concluded low PE (Price / Earnings Per Share) stocks tended to produce higher returns than high PE stocks in the short term (1-4 years) [3]. This view was supported by Basu using data from 1957-71 for US stocks [4].

More recently, at an index level, the likes of Pradeep et al [5], determined that investing at times with a lower PE generated a superior return in comparison with investment at higher PE ratios using 20 years of Indian market data.

In other words, there has been a ‘value anomaly’ within EMH. This is still considered a robust strategy by many market practitioners, who purse ‘value’ strategies that buy stocks with lower near-term PE multiples, in the hope of producing better future returns, in part due to mean-reversion.

A key question is whether this relationships still holds? Arguably, the emergence of the internet and the digital economy has been a game changer. US based venture capitalists, Andreessen Horowitz (A16z), have surmised that ‘Software Is Eating the World’ [6].

Whilst A16z maybe exaggerating and simplifying their core message for impact, they theorize that when investing in technology companies whose growth rates don’t look like that of a ‘normal’ mature company ‘entry multiples don’t matter’

Given the application of data science to stock market analysis remains in its infancy, this study makes use of data visualization techniques to test the ‘value anomaly’ at index (rather than individual stock) level post GFC [7].

The role of the technology sector in producing higher returns is visually considered. As a proxy for world changing innovation and impact, public "mega-cap" stocks (>US$100bn) that were founded no earlier than 1975 are identified. The geographic and sector characteristics of these game changing companies is conceptualized in visual form.

Less can be more. As noted by Arnott et al and Dlotko et al [8][9], in studying stock market returns, the use of more transparent data visualization approaches may be superior at unearthing new perspectives than the application of opaque Machine Learning (ML) techniques, where the mechanism linking input variables to outputs is a 'black box'.

3 Properties of the Data

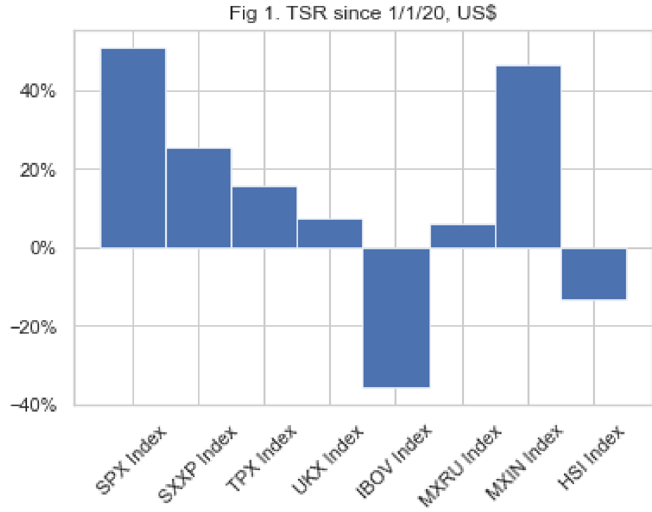
The country level index data analysed in this study focus on:-

- US - the S&P 500 (SPX)
- Europe - Eurostoxx 600 (SKKP)
- Japan – Topix (TPX)
- UK - FTSE-100 (UKX)
- Brazil – Ibovespa (IBOV)
- Russia - MSCI Russia (MXRU)
- India - MSCI India (MXIN)
- China - Hang Seng (Hong Kong, HSI)

Each index is chosen as a broad proxy for the individual country stock market performance, or in the case of Europe regional returns. Whilst alternative indices are available, they are beyond the scope of this study.

The sample periods for this study encompass four distinct time intervals. The first time period covers the recent COVID crisis, from 1st January 2020 to 31st December 2021. At a country index level, daily changes in market valuations are gathered from the Bloomberg and compared in constant currency (US$'s) to identify absolute and relative 'winners' and 'losers' by geography during the crisis (Fig 1).

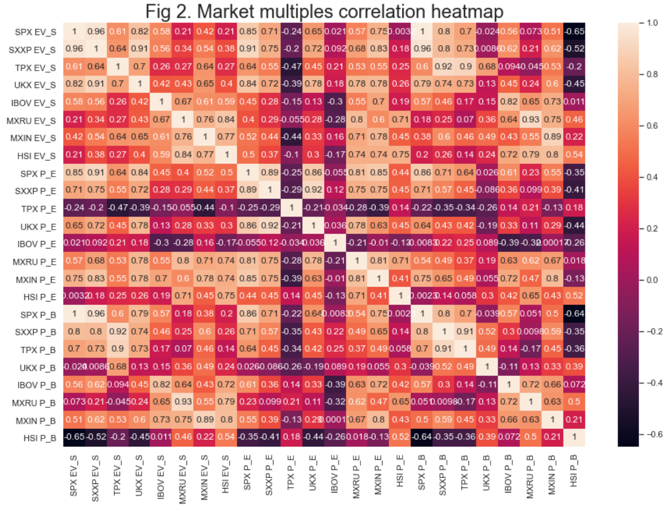
Fig 1. TSR since 1/1/20, US$



The second time series covers the post GFC environment, 1st January 2009 to 31st December 2021, for the same country stock market indices. Trailing 12 month (T12M) starting point relative valuation multiples are identified for each country level index from the Bloomberg.

Two different valuation multiples are inspected; i) EV/Sales (EV = Enterprise Value, defined as Market value of equity less Net Debt) and ii) P/E (Price / Earnings Per Share). This is more comprehensive in nature than many prior academic studies which have focused on P/E or P/B multiples (Fig 2).

Fig 2. Market multiples correlation heatmap



These starting point valuations are set side by side against subsequent 1 year TSR (in US$'s). Longer-term performance horizons were beyond the scope of this study. TSR's are sourced from the Bloomberg. Incomplete data was not a challenge given the comprehensive nature of the Bloomberg.

The third time period covers 1st January 1975 through to 31st December 2021. A screen was run in the Bloomberg to pinpoint publicly listed "mega-cap" companies at end December 2021, in the focus list countries, founded since 1975. For companies that passed these hurdles, data covering the country of listing and sector was gathered. Bloomberg's sector allocations follow a BICS based classification system.

The fourth dataset is ESG focused. Data was hand gathered from the Global Sustainable Investment Alliance (GSIA) trend reports for 2020, 2016 and 2012. This data tracks total Assets under Management (AuM) by geographic region and the proportion of AuM run with an ESG or sustainability anchor.

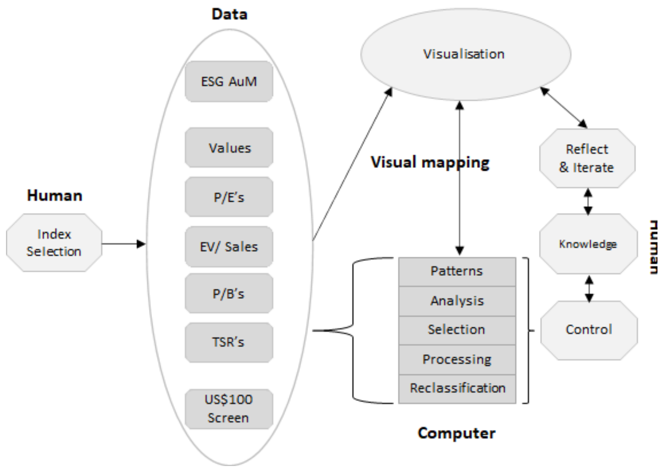
4 Analysis

4.1 Approach

Oftentimes the importance of human judgement in framing choices can be overlooked, from the initial research question, to identification of suitable datasets, to selction of appropriate variables to review. This is powerful when combined with computational processing capability and python libraries that can create engaging visualisations when directed judiciously.

The approach followed is described visually in Fig 3.

Fig. 3. Analysis workflow plan



The first step was to frame the geographic focal point. When thinking about public equity market valuations, there are a very wide range of potential index choices. The obvious index selection for some maybe the country of birth. Others may prefer the largest equity market globally, the US.

Employing human insight, this study took a broader approach, comprisising both developed and developing countries. Within each group, a range of countries were chosen, including the key stock markets globally and the "BRIC" countries. This was to avoid potential country bias from choosing one in isolation.

Within each country there were decisions made about the best equity index to employ. For example, for China, the Hang Seng index was chosen instead of the China A share market. Based on human judgement, the Hang Seng was seen as the best proxy for mainland Chinese companies.

The first dataset, comprising COVID winners and losers on a time series basis, required miniml wrangling to visualise. For the second data set, once the Bloomberg index data had been identified, valuation multiples need to be set on.

According to Investopedia [10], market practitioners use a range of multiples to make comparisons and find the best opportunities. Academic studies often focus on P/E or P/B multiples as longer-term data is available.

Given the sample period for this study, better quality data was available across a wider range of metric. Based on human knowledge, EV/Sales and P/E were chosen as the most relevant, providing the opportunity to cross check. Detailed correlation matrix analysis to aid feature selection followed.

For the screening of "mega-cap" companies, founded since 1975, a boolean expression was used to filter for only those companies founded after 1st January 1975. This provided data based on foundation date. Why 1975 as a start point? That's the year the author of this report was born.

Subsequent manual intervention was required to overwrite anomalous data downloaded from the Bloomberg. For example, Amazon (US) is classified as 'consumer', Tencent (China), 'communications' by the Bloomberg.

For the purpose of this analysis both were reclassified as 'technology'. This study recognises precise definitions are subjective. Human judgment is essential.

From this refined third dataset, the processing power of python was employed to measure the precise interval between company foundation and end-2021.

An iterative process of trial, error, result, perception, reflection and finally new trial ensued with each of these data sets. A range of libraries were used to aid processing and visualisation efforts.

As it was hand-picked, the final ESG based dataset required minimal overlay, beyond visualisation using python.

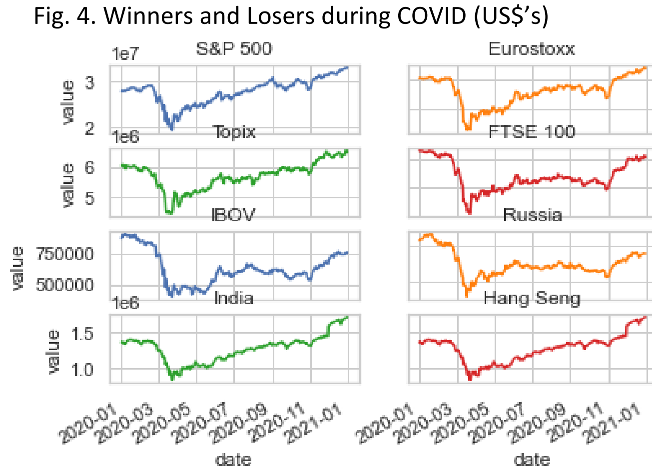
4.2 Process

Taking the Bloomberg data on winners and losers during the COVID pandemic, a stacked subplot using the Matplotlib library was employed. It proved trickier than anticipated. Initially, the plan was to standardise the Y axis scales to aid comparability. Due to the sheer scale of the S&P 500 (US$33 trillion at end 2021), this didn't work out. Visual nuance in smaller markets was lost in the graphic.

S log scale for the Y-axis was tried, to respond to skewness towards the large US value. Unfortunately, this had the opposite impact. Whilst the variation in the BRIC countries could be seen better, material change in the US could no longer be identified (due to the nature of a log scale).

Removing the forced standardisation of the Y axis and the log scale produced Fig 4.

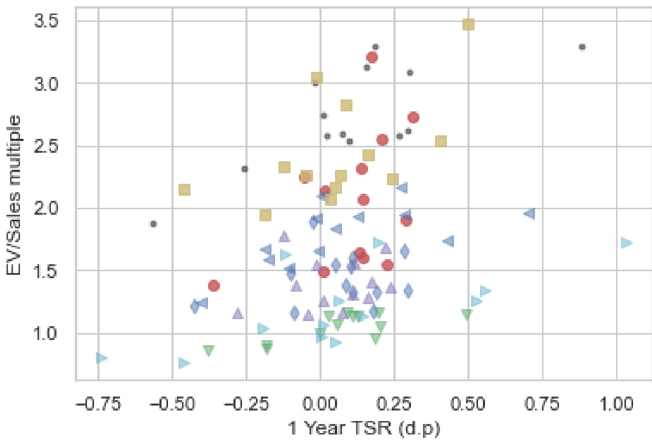
Fig. 4. Winners and Losers during COVID (US$'s)



Many stock markets around the world have increased in value (in US$'s) during the COVID crisis. The US and the Indian stock markets have been the strongest performers (and also the strongest performers since 2009, post GFC). Yet, the US and Indian equity markets are often called out for high near term relative valuation multiples.

EV/Sales multiples and future 1 year TSR were reviewed across each of the indices, using a scatter plot with the matplotlib library (Fig 5). Different regions were given distinct colours and markers. For example, the US in red circles, the Hang Seng in yellow squares and India in black dots.

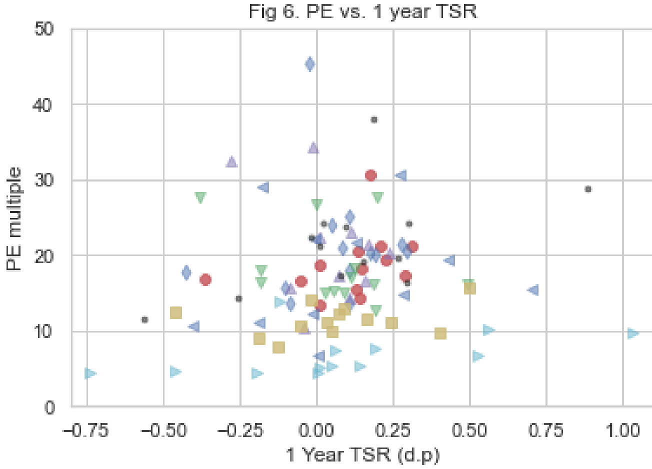
Fig 5. EV/Sales vs. 1 year TSR



Somewhat curiously a pattern appeared to be evident where higher starting point valuations, (the Y-axis, EV/Sales) positively correlated with higher subsequent TSR and vice-versa. For example, the US, Indian and Hong Kong markets all appear to have posted higher returns from higher valuations.

The primary disadvantage of using EV/Sales is its lack of reference to differences in profitability. A P/E approach was utilised to see if there was any material contrast (Fig 6). The same colour and ticker mark formatting was applied.

Fig 6. PE vs. 1 year TSR



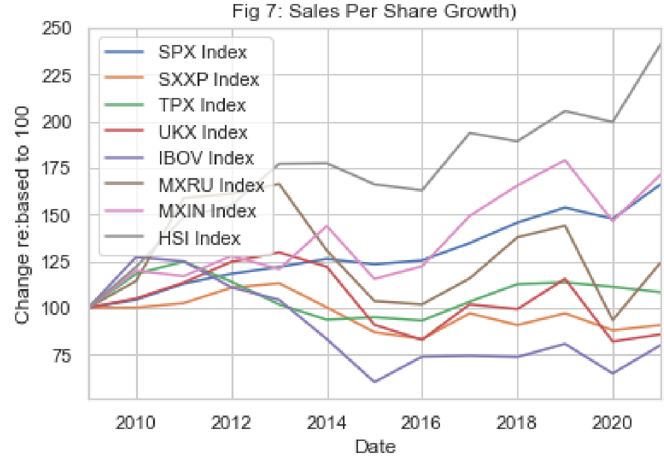
The y-axis size was limited to reflect the presence of outliers that distorted the visualization.

Perhaps the results in Fig 6 are less clear cut than the EV/Sales scatter plot, but nonetheless the sweep from bottom left still appears to be evident. Across the sample, a higher starting point PE valuation multiple appears to have resulted in stronger subsequent performance and vice-versa.

If it's not starting point valuations, are there other variables that might better explain future TSR? 'Tech' weightings as a percentage of each index offer potential insight. At end 2021, near 30% of the S&P500 was tech, vs 1% for the FTSE-100.

Re-based to 100 to aid comparability, a time-series analysis of 'Sales per share' by index is instructive (Fig 7). With the exception of the Hang Seng, the strongest performing markets had the highest growth. NB. It is possible the Hang Seng is an outlier because of a regulatory crackdown by the Chinese government on tech companies like Alibaba and Tencent.

Fig 7: Sales Per Share Growth)



Structurally, the tech sector can be viewed as a proxy for innovation. Unlike 30 years ago, where being a tech company had a relatively modest impact (e.g. selling servers to a business customer), successful tech companies today pervade every aspect of modern life ('to Google' is a transitive verb).

Absent adverse regulation, successful tech companies don't just disrupt existing end-markets (e.g. Google's impact on printed newspapers, magazines and linear broadcast TV stations), they also offer the promise of much higher growth.

Sales growth for the US, Indian and Chinese markets has been significantly higher than for Europe, Japan, Brazil or Russia post GFC. As a result, tech can command higher near-term valuation multiples reflecting its growth prospects.

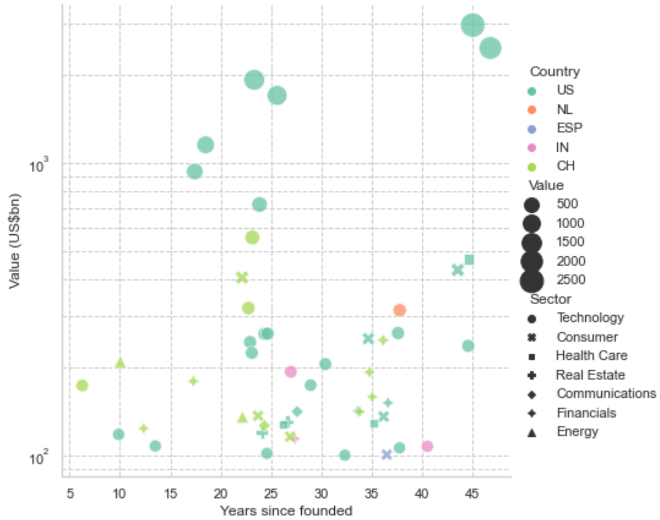
This prompted a search for publicly listed companies created within the last 46 years ago, that had a market value >US$100bn at end-21. Put simply, which countries are innovating and creating mega value at the same time by sector?

With the data loaded and time elapsed calculated with python, experimentation with different chart types began, with the aim of creating an engaging visualization.

The Matplotlib and Seaborn libraries were both used. With the first effort it was difficult to distinguish between countries, sectors or company sizes. The scale impact of some very large companies (>US$500bn in market cap) were distortions.

A log scale for the Y axis was incorporated to reduce the skew. A size factor was introduced to better capture differences in market value in the scatter. A colour scheme was grouped by region to further improve the quality of insight the scatter plot was able to provide. Finally, ticker marks were introduced to more clearly differentiate between sectors. The aggregate result of this trial and error process is presented in Fig 8.

Fig 8. Companies >US$100bn in value since 1975



Geographically speaking, Fig 8 reveals the supremacy of the US (the light blue market) over the sample period as entrepreneurial innovators, capable of consistently producing new “mega-cap” companies on public equity markets.

Despite having a significantly larger population than the US, Europe has only managed to beget two “mega-cap” companies, founded since 1975. One is from the Netherlands, ASML (a titan in semiconductor industry), the other Spain, Inditex (a clothes retailer better known as Zara).

Sadly, the UK and Japan can’t claim to have spawned a single new “mega-cap” since 1975 (for the UK Vodafone was once above this level but has long since lost its lustre). The same is true for Brazil and Russia, providing more potential fodder to the ‘resource curse’ lobby.

From the developing world, China (the green markers in Fig 8) appears to have produced the most “mega-cap” companies founded since 1975 (15 in total, the largest of which is Tencent, a tech firm).

NB. Prosus, part owner of Tencent, listed in the Netherlands is excluded to avoid double counting). India is also present in the visualization (the purple marker), with 3 companies, 2 of which are tech firms.

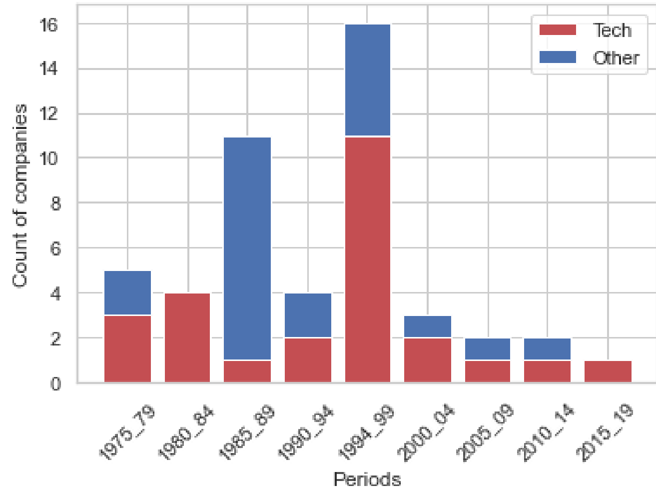
From Fig 8, the size variable clearly conveys that a handful of companies founded in the sample period have gone onto become very big (measured in trillions of dollars). Apple and Microsoft are good examples, taking decades to get there.

There are only three companies founded in the past 10 years that have gone onto have public market values >US$100bn.

The tickers show the absolute and relative importance of the tech sector (circles) in driving value creation. Put another way, tech has dominated in terms of the number of new publicly listed “mega-cap” companies since 1975.

Given possible challenges counting values in Fig 8, a stacked bar chart was run (Fig 9).

Fig 9. Count of US$100bn companies founded by 5 year period



Several important points jump out from this simple graphic. Firstly, only 48 firms have been founded since 1975 that were public “mega-caps” at end-2021. That's a very small number.

Of these 48 firms, 26 are tech companies, or 54% of the total. This appears to underline the importance of the tech sector to the global economy and valuations.

Intriguingly, the most 'innovative' 5 year periods in our sample period are between 1985-89 and 1994-1999. In these years 11 and 16 companies respectively were founded that went onto become “mega-cap” stocks.

For this second period (1994-1999), it is important to note the emergence of the TMT bubble in 1999 (reaching its zenith in March-2000). This period in financial market history has been much commented on and scorned. For example, in ‘Irrational exuberance’ Shiller called out the bubble, based on an analysis of long-term average PE multiples (the Shiller PE, not to be confused with the T12M PE used in this study) [11].

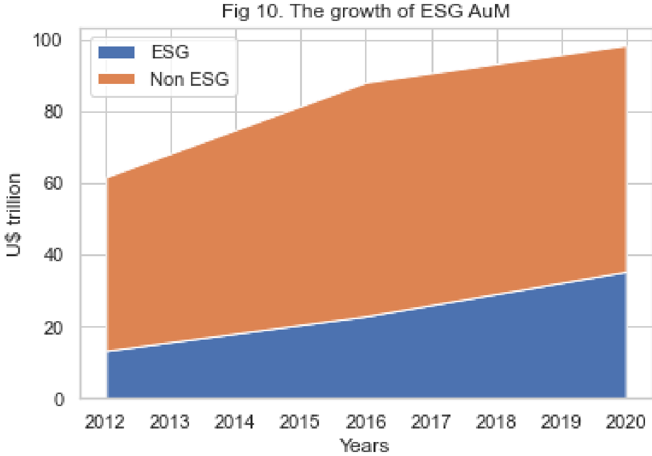
Yet, with the benefit of hindsight, Fig 9 allows us to discern that the run up to this time was an unrivalled period of innovation, defined in terms of the number of new companies founded that went onto become “mega-caps” by end 2021.

Whilst individual companies with flimsy business models were undoubtedly overvalued during this period, Fig 9 gives a sense of what caused all the excitement; a feeling of massive structural change incoming. Arguably, we see the fruits today.

From the sample countries covered in this study, the only countries excluded from this analysis that have produced a US$100bn company since 1975 are Canada, with Shopify (founded in 2006) and Taiwan with Taiwan Semiconductor, (founded in 1987). If both were included, it would only add further weight to the analysis (i.e. more tech).

Using the GSIA reports this study also briefly explored the potential impact from growth in EG funds. By 2020, the latest figure available, US$35 trillion were aligned with an ESG purpose, from US$13 trillion in 2012 (13% CAGR). A stacked area chart was created (Fig 10) covering 2012-2020.

Fig 10. The growth of ESG AuM



Interestingly, growth in ESG assets in absolute terms has been strongest in the US. This could be important. ESG investors may have negative screens in place that stop them from investing in harmful business models, for example the tobacco sector or those with large carbon emissions (e.g. oil stocks, miners, banks etc). Energy, mining and banks sectors tend to trade at lower valuation multiples.

4.3 Results

Fig 11 shows the correlation between EV/Sales and future return (1 year TSR) by index.

In the US the correlation between starting EV/Sales valuation and 1 year TSR is 0.43. The relationship appears weaker for Europe (r = 0.19) and the UK (r = 0.17). The stronger positive correlations observable in Japan (r = 0.74), Brazil (r = 0.65), Russia (r = 0.68) and India (r = 0.75) suggest higher starting point valuations have resulted in stronger 1 year returns.

A similar conclusion is evident focused on PE (Fig 12). Correlations are weak across all indices. For example, the starting point PE for the US has a mild positive correlation of 0.32 to 1 year TSR. In Europe the correlation is near 0.

Fig 11. EV/Sales correlation heatmap

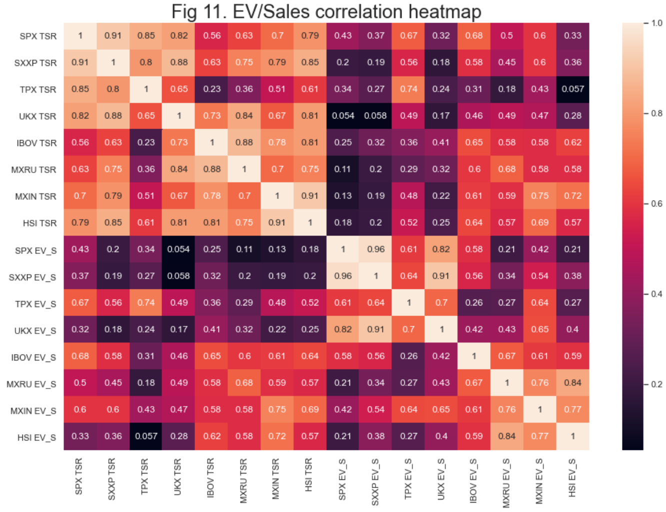
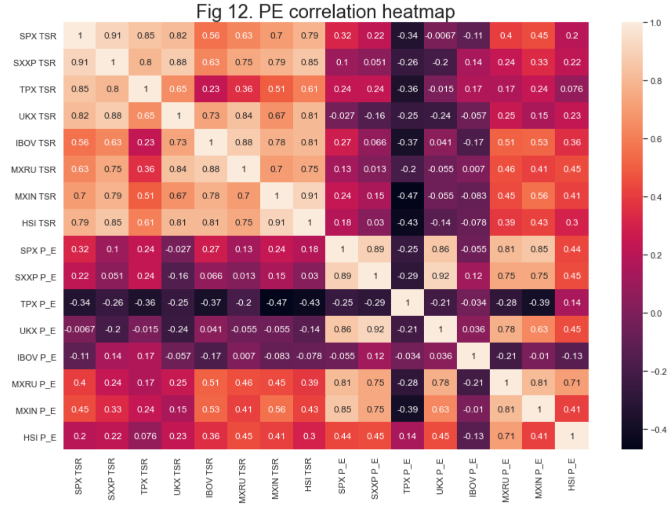


Fig 12. PE correlation heatmap



This study's findings strongly contradict earlier academic work on the EMH, in particular the 'value anomaly'. During the sample period, the signal power of low starting point valuation multiples to a range of indices appears limited. This is a salient result.

The message is clear, investors should be careful using lower short-term valuation multiples (EV/Sales or PE) as predictive of subsequent 1 year total shareholder returns.

5 Critical reflection

Given the widespread acceptance of the 'value anomaly' within academic and professional audiences, the results presented in this study maybe surprising. That said, the core assumptions economists recurrently make to underpin their theories both undermine their practicability and limit opportunity to test their efficacy. An example of this is the assumption of rationality or in finance risk/return optimization [12].

Looking forward there are five distinct areas within this study that could benefit from further research effort, subject to accessible data being made available.

Firstly, the horizon period for assessing returns could be changed. As time passes, 3 and 5 year periods could be used. 1 year returns maybe too short-term in nature.

Secondly, if data could be obtained that showed the tech sectors weighting in each index on an annual basis, this could be tested as an explicit predictor variable of performance using regression analysis. This study did not have access (the index providers charge for it).

Thirdly, given the apparent importance of the tech sector in the modern economy, the predictive power of valuation multiples on future performance could be considered at a sector rather than country level.

Fourthly, the emergence of ethical savers appears to be fundamentally changing the capital market landscape. These investors believe businesses should have ambitions beyond profit or general financial performance. If enough investors get behind the ESG mantra, society's tacit approval for harmful businesses to operate in public markets could be challenged. Arguably, we already see evidence of this in the tobacco sector.

As a result, ESG AuM growth could be a significant predictor variable of higher near-term multiples and higher subsequent returns for ESG friendly stocks (e.g. the tech sector which often has low carbon emissions), and lower valuation multiples and weak on-going performance for harmful firms. Unfortunately, this study did not have access to a daily data series stretching back to 2009 to test this hypothesis with multiple regression analysis.

Finally, re-testing the results of this analysis periodically could be worthwhile. Since 2009, the major central banks around the world have run zero interest policies (ZIRP) with official inflation measures muted. This appears to be changing. It is possible the 'value anomaly' re-asserts itself in a rising interest rate environment.

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References

The list below provides examples of formatting references.

[1] E. F. Fama and K. R. French, 'The Capital Asset Pricing Model: Theory and Evidence', *Journal of Economic Perspectives*, vol. 18, no. 3, pp. 25–46, Aug. 2004, doi: 10.1257/0895330042162430.

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