



LOS ANGELES
CAPITAL

HOW TECHNOLOGY IS CHANGING INVESTING

SEPTEMBER 2024



OVERVIEW

- Three considerations when thinking about new technology and the investment process
- Examples of applications of new technology in the investment process
 - Turning unstructured data into consumable forms and the construction of peer groups
 - Improving investment signal construction using peer groups
 - Expanding investment ideas using new technology
- Thinking of Artificial Intelligence (A. I.) and technology as an investment theme



THREE CONSIDERATIONS FOR THE APPLICATION OF NEW TECHNOLOGIES IN THE INVESTMENT PROCESS

1. The investment problem remains the same (and equally difficult!)
2. New technologies face some challenges when addressing the investment problem:
 - The presence of noise in the data
 - The data available for training a model may only represent a small fraction of possible future states
3. When carefully applied, new technologies can lead to refined investment research and greater efficiency in the discovery of new investment ideas



MACHINE LEARNING AND FINANCIAL DATA

- Artificial Intelligence (A. I.) refers to the ability of a machine to simulate human intelligence
- Machine learning is a branch of A. I. that focuses on the development of algorithms that “learn” from data without explicit instruction

“Machine learning refers to a diverse collection of high-dimensional models for statistical prediction combined with regularization methods to help mitigate overfitting and guide model selection (Gu et. al. 2020)”



ML models are most effective when we have a large amount of data or high signal-to-noise ratio (or both).



There are two aspects of ML that are particularly useful for financial data:



Financial data frequently has neither, so it is important to understand the limitations of ML and choose the right tool for the job.

1

Regularization

Avoid overfitting forecasts and signal/model selection.

2

Natural Language Processing (NLP)

Extract information from unstructured text.



NATURAL LANGUAGE PROCESSING (NLP)

A branch of ML that teaches computers to understand written or spoken text.

There are many NLP models for different types of language tasks: Sentiment Analysis, Information Extraction, Machine Translation, Speech Recognition, Chatbots, etc.

These models can be trained on any body of text (e.g. financial filings, earnings call transcripts, corporate reports.)

NLP Models are particularly useful because we can analyze large amounts of unstructured data for insights into firm fundamentals and characteristics using a quantitative approach.



THE PROCESSING OF TEXT – A SIMPLE EXAMPLE

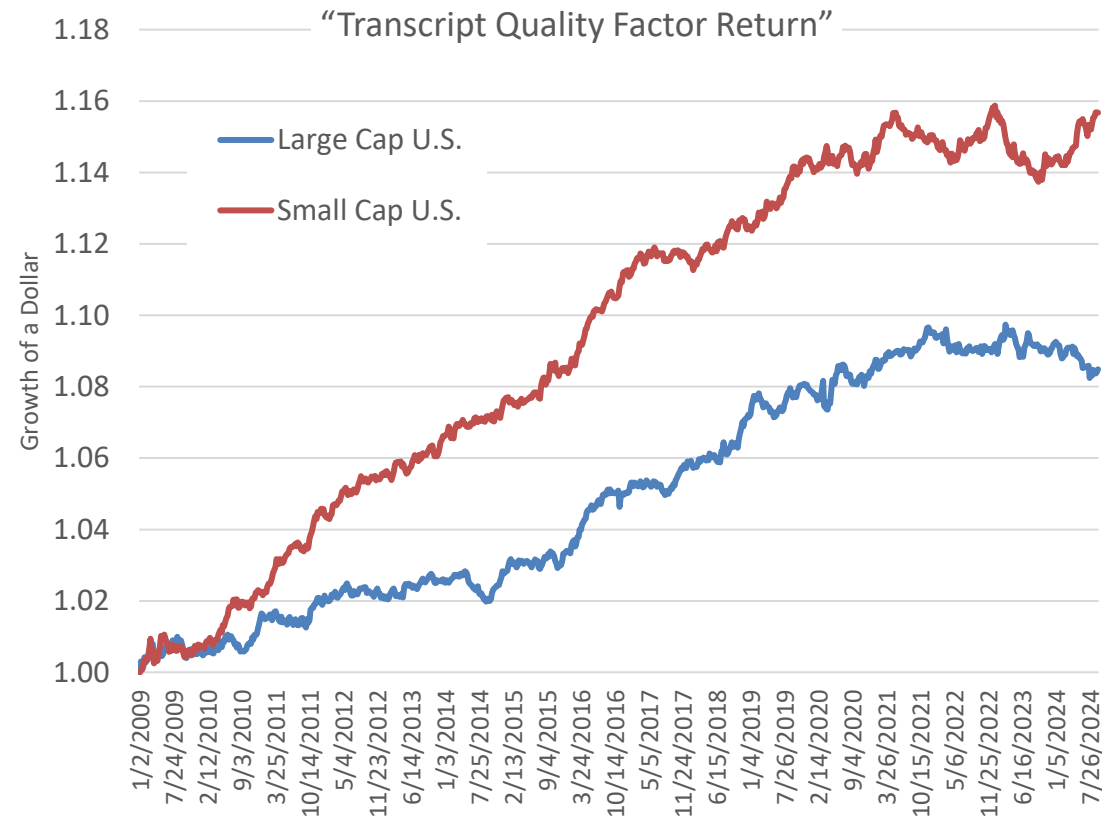
Even simple techniques can be used to transform text data into a form the computer can consume

Assess “transcript quality” through text analysis

- Sentiment/polarity
- Objectivity/digit-to-letter ratio
- Transparency/readability

Features:

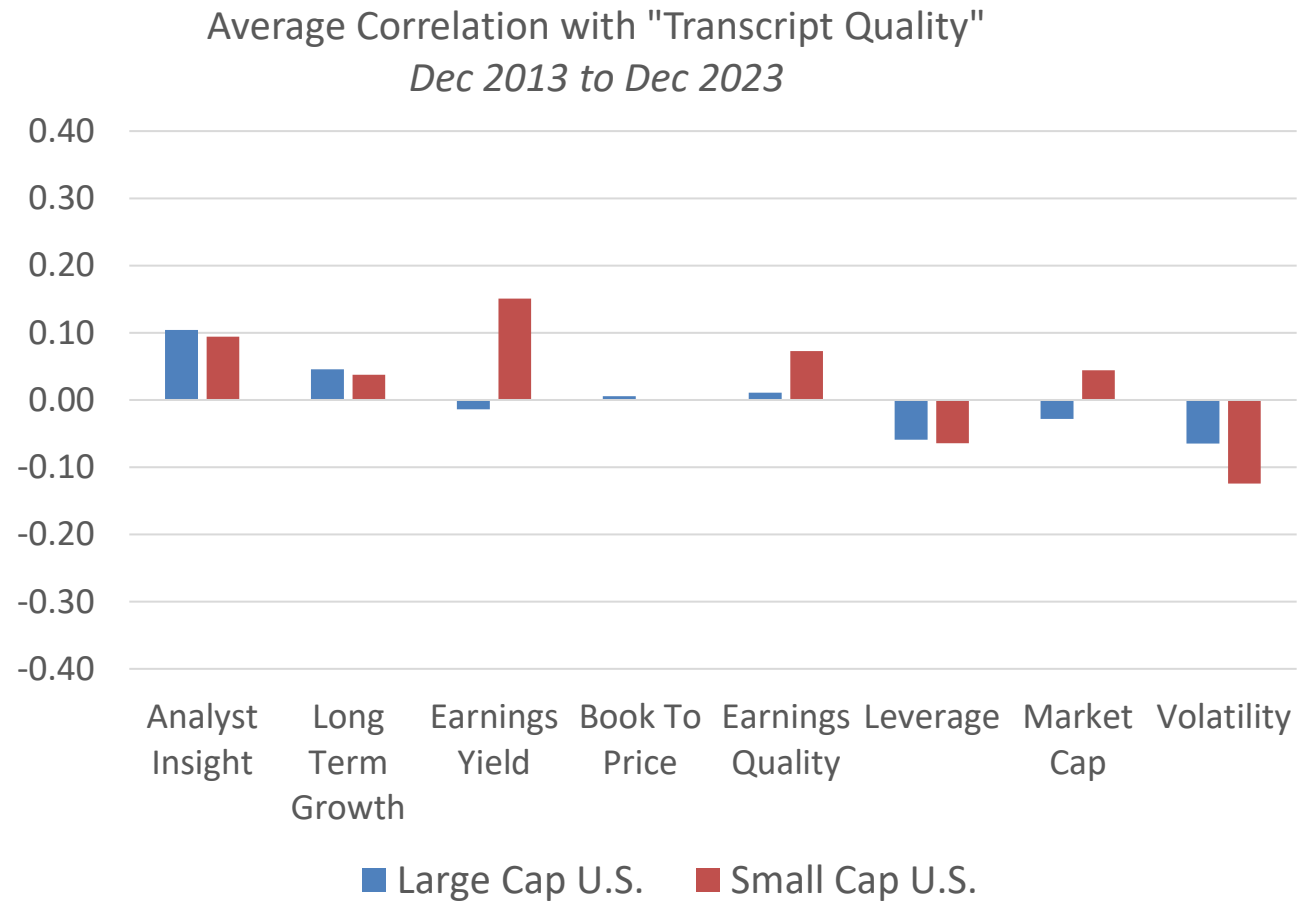
- Stable return
- Slow signal decay
- Uncorrelated with other factors





THE PROCESSING OF TEXT – A SIMPLE EXAMPLE

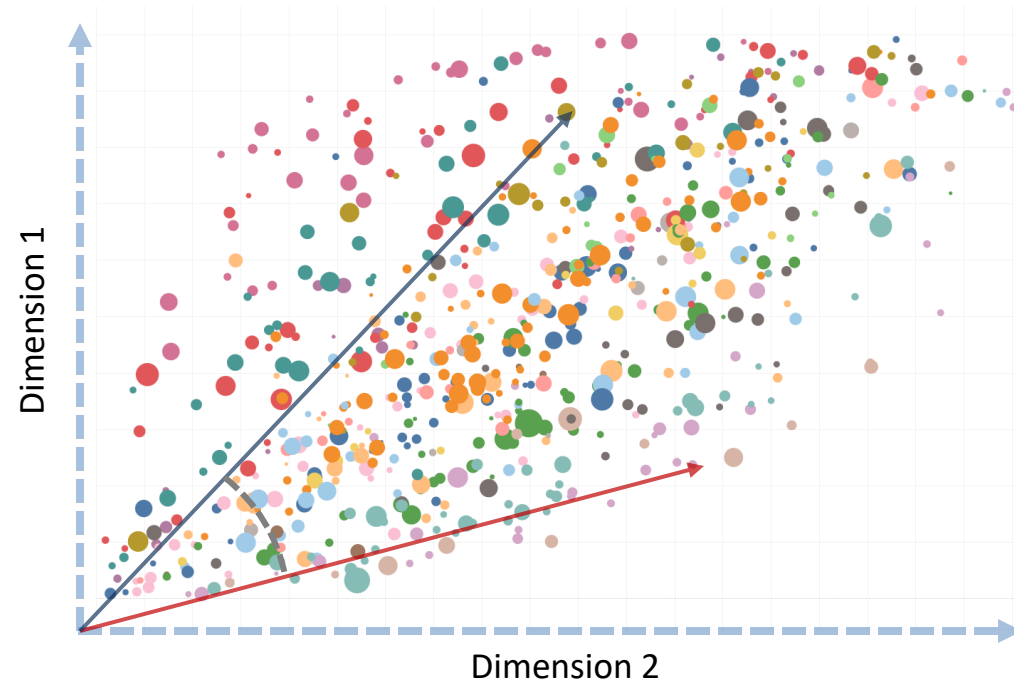
Shows low average correlation with other known drivers of return





BUILDING BETTER INVESTMENT INSIGHTS: THE DEVELOPMENT OF PEER GROUPS

- Having turned documents into a consumable vector peer companies can be found by asking “*how similar are the vectors?*”



- Alternative forms of text processing result in more nuanced comparisons:

	advertis	video	cabl	lobbi	app	tv	googl	voic	polit	proxi	movi	film	theme	subscrib	prime
Comp A	0.154	0.206	0.443	0.079	0.030	0.117	0.005	0.099	0.038	0.026	0.100	0.205	0.079	0.118	0.036
Comp B	0.153	0.077	0.017	0.043	0.106	0.027	0.640	0.023	0.024	0.033	0.008	0.004	0.010	0.006	0.014



BUILDING BETTER INVESTMENT INSIGHTS: THE DEVELOPMENT OF PEER GROUPS

- Both machine learning and traditional metrics can be used to identify peers:
 - Examples of Natural Language Processing (NLP) techniques for analysis of earnings call transcripts:
 - Term Frequency Inverse Document Frequency (TFIDF) *identifies the common occurrence of important words in transcripts*
 - Document Vectorization – *employs a neural network to understand the semantic context of words in the transcript*
 - Topic Modeling – *aims to learn common topics of discussion from the corpus of all transcripts*
 - More traditional metrics may include:
 - Insight from analyst co-coverage
 - Sub-industry classification
 - Risk exposures
- Peer companies are those that are “similar” along the above dimensions
- Similarities across multiple dimensions can be combined into a single composite measure to build a “peer group” for each parent company



IDENTIFYING PEERS: COMPOSITE MEASURE ILLUSTRATIVE EXAMPLE

Adidas - High Confidence Peers as of 10/31/2022							
PEER COMPANY	NLP 1	NLP 2	NLP 3	ANALYST	RISK	SUBIND	COMPOSITE
Hugo Boss Ag	0.33	0.96	0.98	0.91		0.91	0.72
Puma Se	0.78	0.92	1.00	0.92		0.41	0.71
Nike Inc	0.74	0.98	1.00	0.59	0.77	0.37	0.69
V F Corp	0.52	0.91	0.99	0.49		0.88	0.69
Burberry Group		0.89	0.96	0.57	0.49	0.93	0.65

Adidas - Low Confidence Peers as of 10/31/2022							
PEER COMPANY	NLP 1	NLP 2	NLP 3	ANALYST	RISK	SUBIND	COMPOSITE
Macys Inc.			0.21	0.26			0.07
Hershey Foods Corp		0.15					0.02
Mcdonalds Corp					0.13		0.02
Bath & Body Works Inc		0.11		0.02			0.02
Best Buy Inc			0.05				0.01

Numbers in the above tables are percentile ranks of the similarity measures using various methodologies to identify peers. The composite value is an average of those numbers. This analysis is for illustrative purposes to provide examples of how the composite peer-group measure cleanses out the “noise” across models by giving low (high) scores to peer companies with little (more) agreement across models.



IDENTIFYING PEERS

- MSCI announced a change to its GICS classification scheme effective March 2023:
 - Data & Processing & Outsourced Services companies were reclassified *from Information Technology to Industrials and Financials*:
 - *E.g. Companies offering payment related transaction and processing services were reclassified to the Human Resources and Employment sub-sector*
 - Select companies that mainly sell consumable merchandise were moved *from Consumer Discretionary to Consumer Staples*:
 - *E.g. Retailers that generate most of their revenue from consumable staple items were grouped with other hypermarkets and supercenters*
- The peer identification methodology captures the economic linkages that underlie these changes in GICS reclassification



PEER REPRESENTATIONS OF PARENT COMPANIES

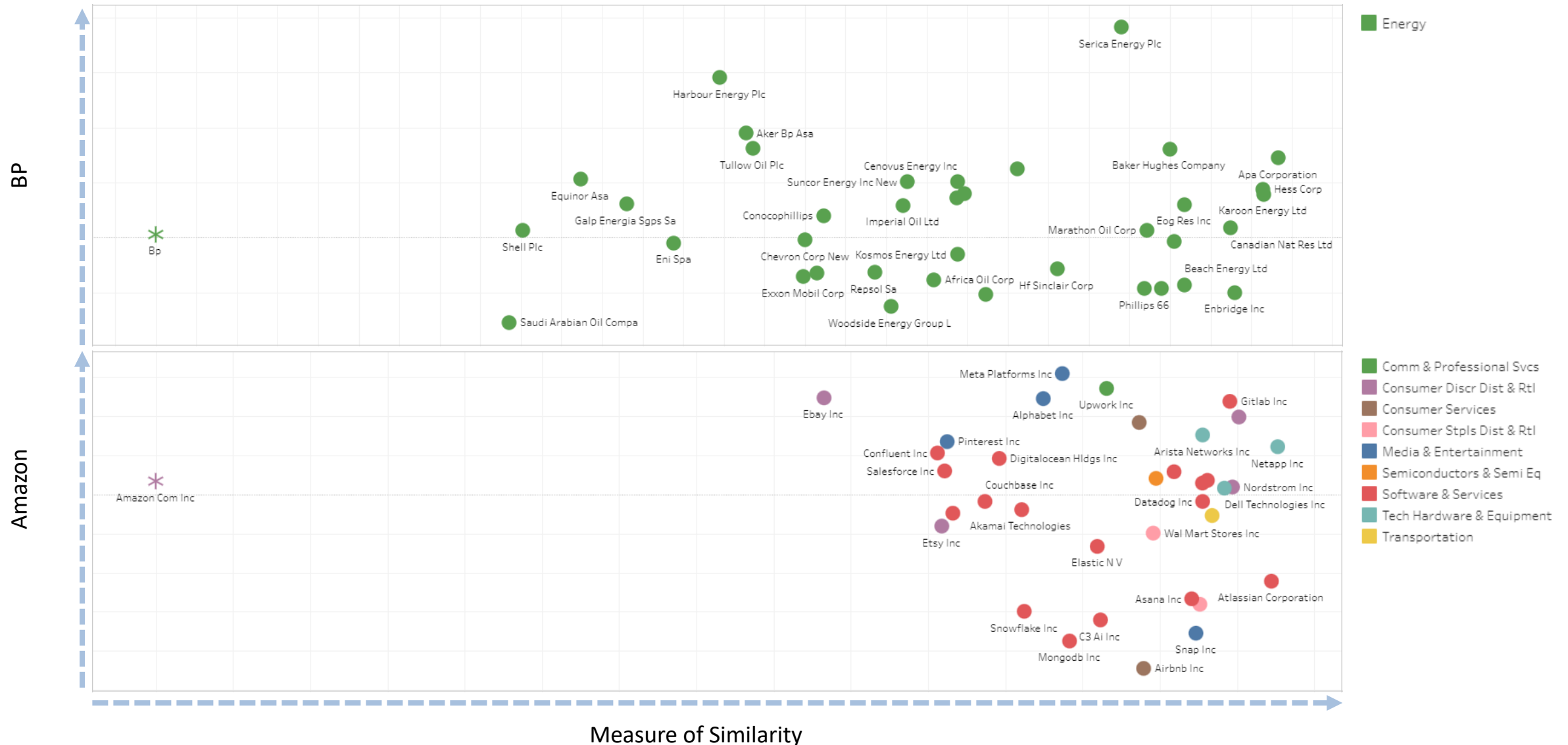
Automatic Data Processing (ADP) -- Sector: Information Technology; Sub-Industry: Data Proc & Outsourced Services ⇨ Sector: Industrials; Sub-Industry: Human Resrc & Employ Svcs								
12/31/2020			12/31/2021			12/30/2022		
Peer	Peer Sector	Peer Sub-Industry	Peer	Peer Sector	Peer Sub-Industry	Peer	Peer Sector	Peer Sub-Industry
Paychex Inc	Information Technology	Data Proc & Outsrcd Svcs	Paychex Inc	Information Technology	Data Proc & Outsrcd Svcs	Paychex Inc	Information Technology	Data Proc & Outsrcd Svcs
Fiserv Inc	Information Technology	Data Proc & Outsrcd Svcs	Genpact Limited	Information Technology	Data Proc & Outsrcd Svcs	Ss&C Technologies Hldgs	Information Technology	Data Proc & Outsrcd Svcs
Trinet Group Inc	Industrials	Human Resrc & Employ Svcs	Paylocity Hldg Corp	Information Technology	Application Software	Trinet Group Inc	Industrials	Human Resrc & Employ Svcs
Conduent Inc	Information Technology	Data Proc & Outsrcd Svcs	Paycom Softwareinc	Information Technology	Application Software	Paycom Softwareinc	Information Technology	Application Software
Gartner Group Inc Ne	Information Technology	IT Consulting & Other Svc	Trinet Group Inc	Industrials	Human Resrc & Employ Svcs	Fiserv Inc	Information Technology	Data Proc & Outsrcd Svcs
Sykes Enterprises In	Information Technology	Data Proc & Outsrcd Svcs	Insperty Inc	Industrials	Human Resrc & Employ Svcs	Fidelity Natl Inform	Information Technology	Data Proc & Outsrcd Svcs
Dxc Technology Co	Information Technology	IT Consulting & Other Svc	Fiserv Inc	Information Technology	Data Proc & Outsrcd Svcs	Alight Inc	Industrials	Human Resrc & Employ Svcs
Fleetcor Technologies I	Information Technology	Data Proc & Outsrcd Svcs	Fleetcor Technologies I	Information Technology	Data Proc & Outsrcd Svcs	Paylocity Hldg Corp	Information Technology	Application Software
Visa Inc	Information Technology	Data Proc & Outsrcd Svcs	Trueblue Inc	Industrials	Human Resrc & Employ Svcs	Insperty Inc	Industrials	Human Resrc & Employ Svcs
Genpact Limited	Information Technology	Data Proc & Outsrcd Svcs	Gartner Group Inc Ne	Information Technology	IT Consulting & Other Svc	Ceridian Hcm Hldg Inc	Information Technology	Application Software

Dollar General -- Sector: Consumer Discretionary; Sub-Industry: General Merchandise Store ⇨ Sector: Consumer Staples; Sub-Industry: Hypermarkets and Super Centers								
12/31/2020			12/31/2021			12/30/2022		
Peer	Peer Sector	Peer Sub-Industry	Peer	Peer Sector	Peer Sub-Industry	Peer	Peer Sector	Peer Sub-Industry
Dollar Tree Inc	Consumer Discretionary	General Merchandise	Ollies Bargain Outlt HI	Consumer Discretionary	General Merchandise	Dollar Tree Inc	Consumer Discretionary	General Merchandise
Sprouts Fmrs Mkt Inc	Consumer Staples	Food Retail	Dollar Tree Inc	Consumer Discretionary	General Merchandise	Ollies Bargain Outlt HI	Consumer Discretionary	General Merchandise
Lowes Cos Inc	Consumer Discretionary	Home Improvement	Lowes Cos Inc	Consumer Discretionary	Home Improvement	Tractor Supply Co	Consumer Discretionary	Specialty Stores
O Reilly Automotive Inc	Consumer Discretionary	Automotive Retail	Big Lots Inc	Consumer Discretionary	General Merchandise	Lowes Cos Inc	Consumer Discretionary	Home Improvement
Big Lots Inc	Consumer Discretionary	General Merchandise	Target Corp	Consumer Discretionary	General Merchandise	Dollarama Inc	Consumer Discretionary	General Merchandise
Tractor Supply Co	Consumer Discretionary	Specialty Stores	Advance Auto Parts	Consumer Discretionary	Automotive Retail	Big Lots Inc	Consumer Discretionary	General Merchandise
Target Corp	Consumer Discretionary	General Merchandise	Dollarama Inc	Consumer Discretionary	General Merchandise	Bjs Whsl Club Hldgs Inc	Consumer Staples	Hypermarkets & Super
Advance Auto Parts	Consumer Discretionary	Automotive Retail	Tractor Supply Co	Consumer Discretionary	Specialty Stores	Five Below Inc	Consumer Discretionary	Specialty Stores
Ollies Bargain Outlt HI	Consumer Discretionary	General Merchandise	O Reilly Automotive Inc	Consumer Discretionary	Automotive Retail	Autozone Inc	Consumer Discretionary	Automotive Retail
Home Depot Inc	Consumer Discretionary	Home Improvement	Sprouts Fmrs Mkt Inc	Consumer Staples	Food Retail	Grocery Outlet Hldg Cor	Consumer Staples	Food Retail



PEER REPRESENTATIONS OF PARENT COMPANIES

- Peer groups can provide a more nuanced representation of the economic exposures of a parent company

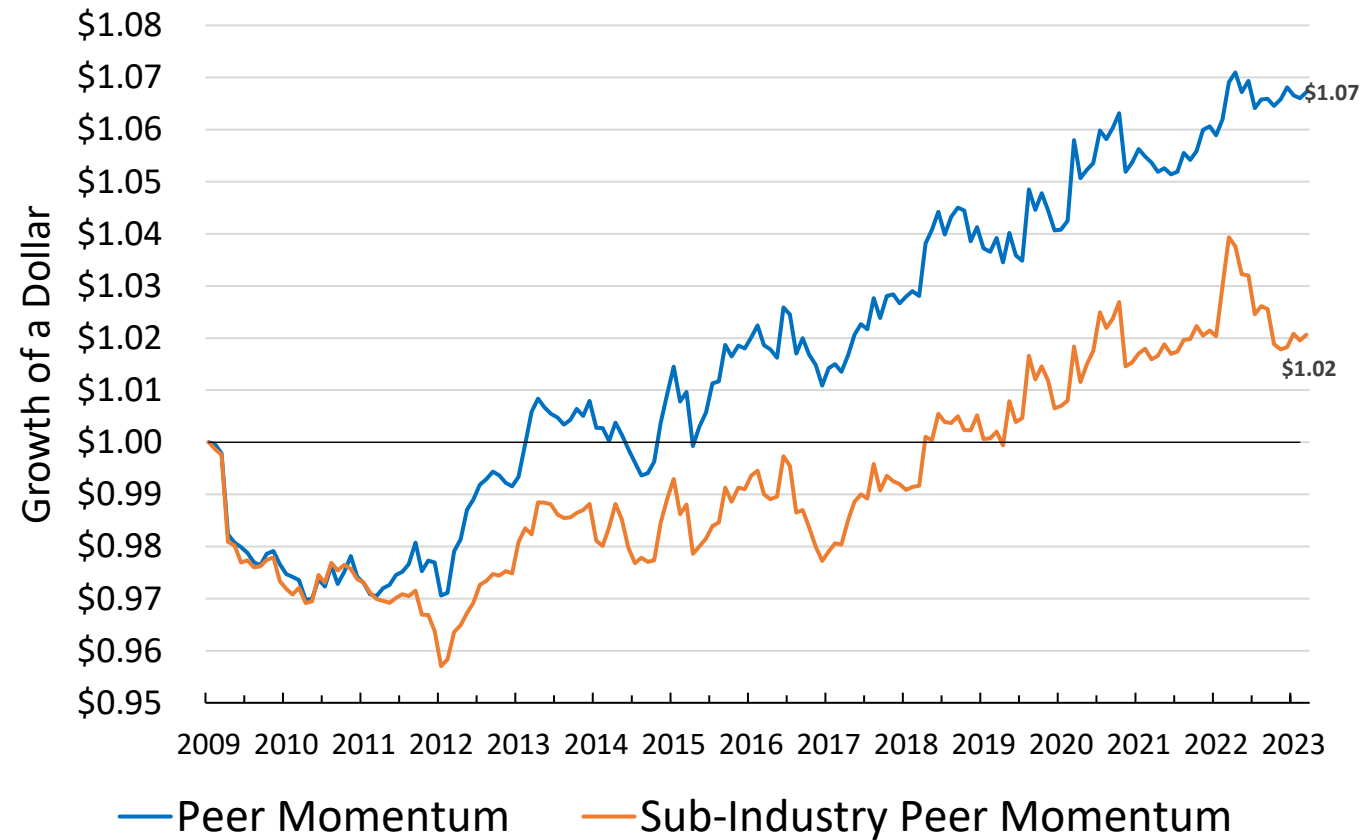




CUSTOM PEER GROUP MOMENTUM VERSUS INDUSTRY MOMENTUM

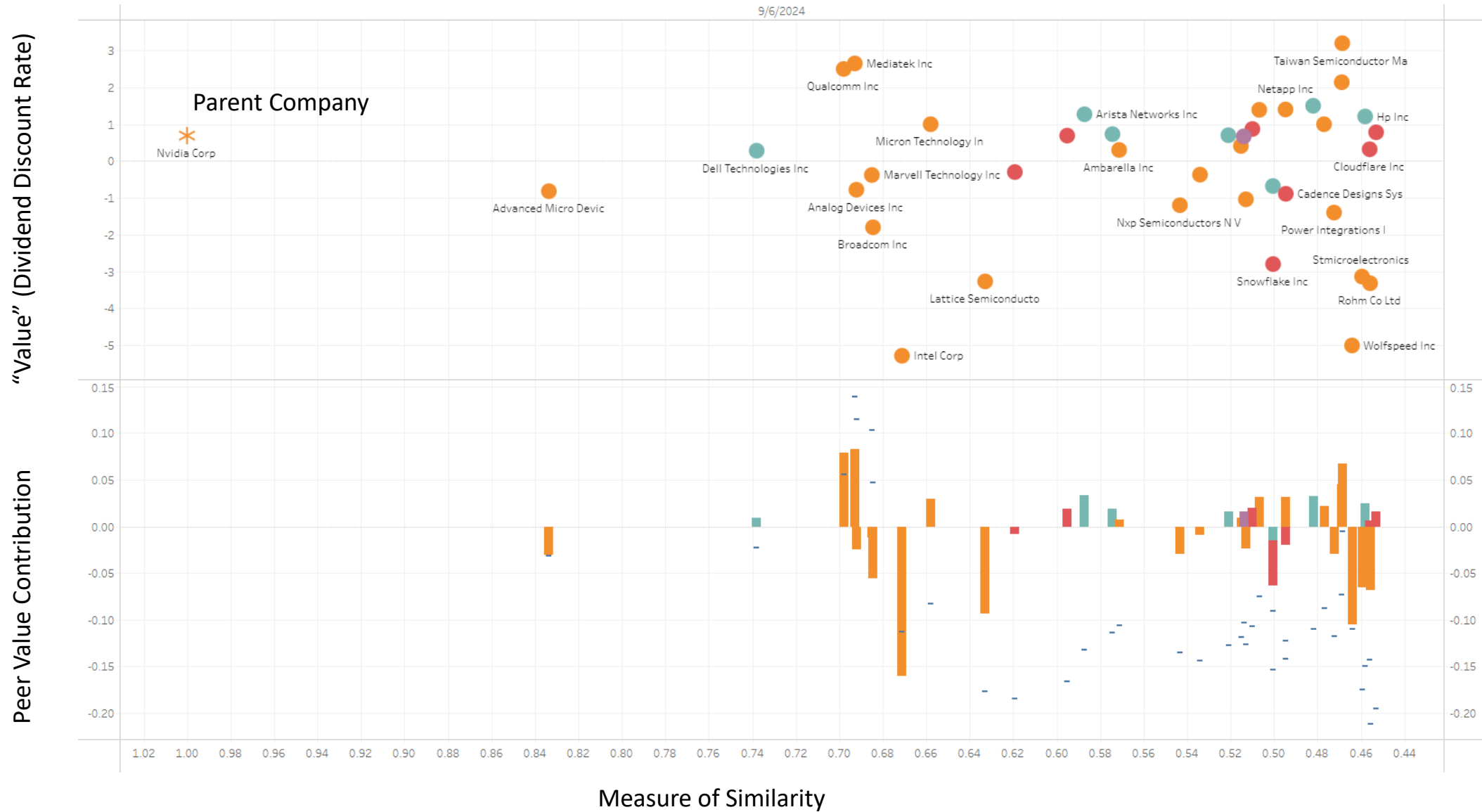
Cumulative Total Return Illustration to \$1 Invested

February 2009 - March 2023





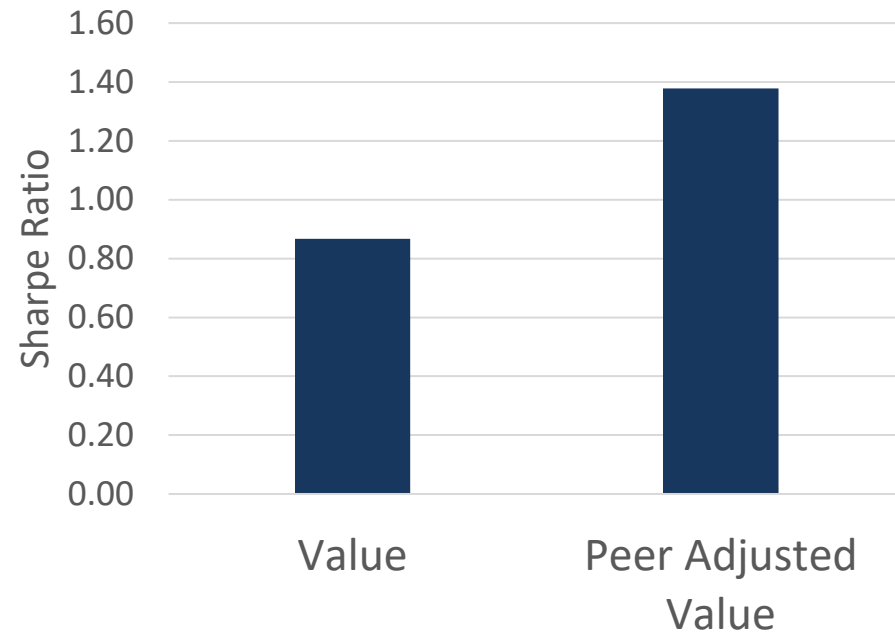
USING PEER GROUP COMPARISON IN THE INVESTMENT DECISION: PEER VALUE



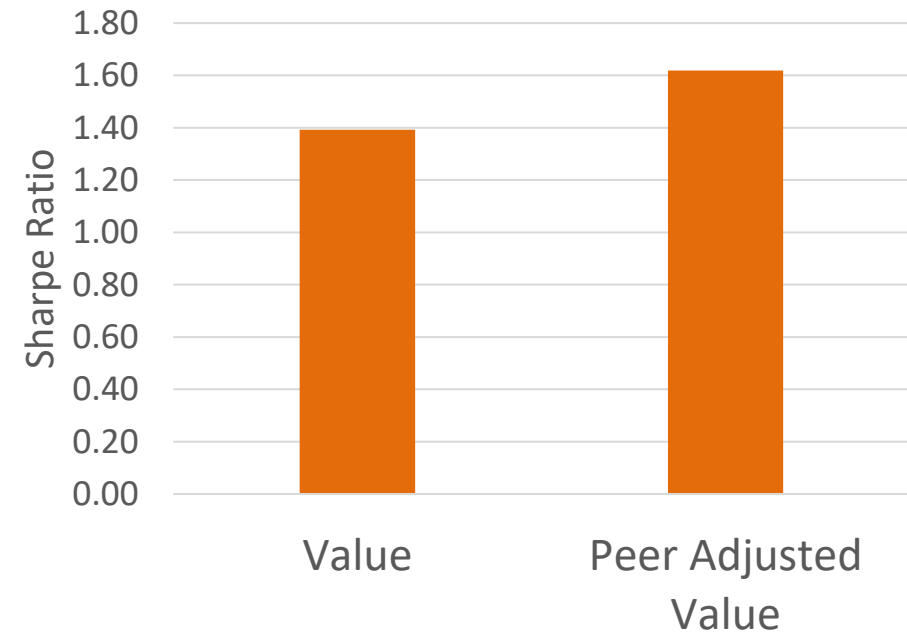


USING PEER GROUP COMPARISON IN THE INVESTMENT DECISION: PEER VALUE

Large Cap Opportunity Set



Z-Scored Signal

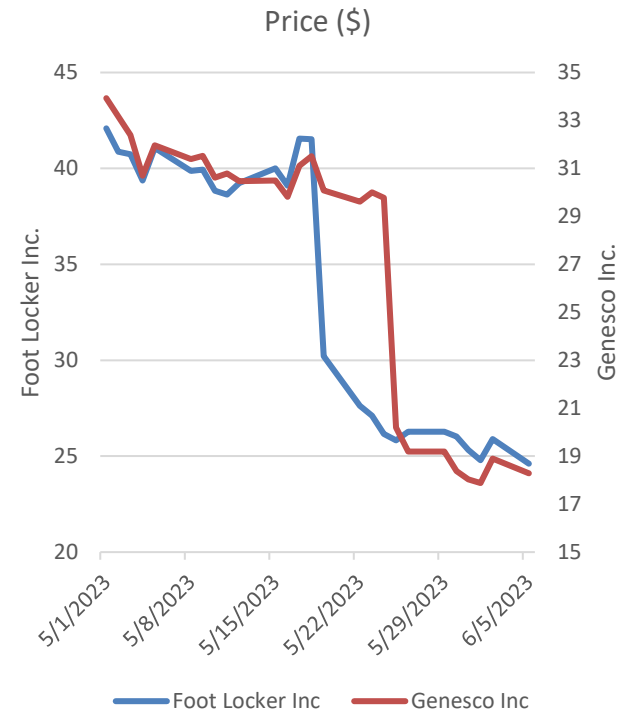
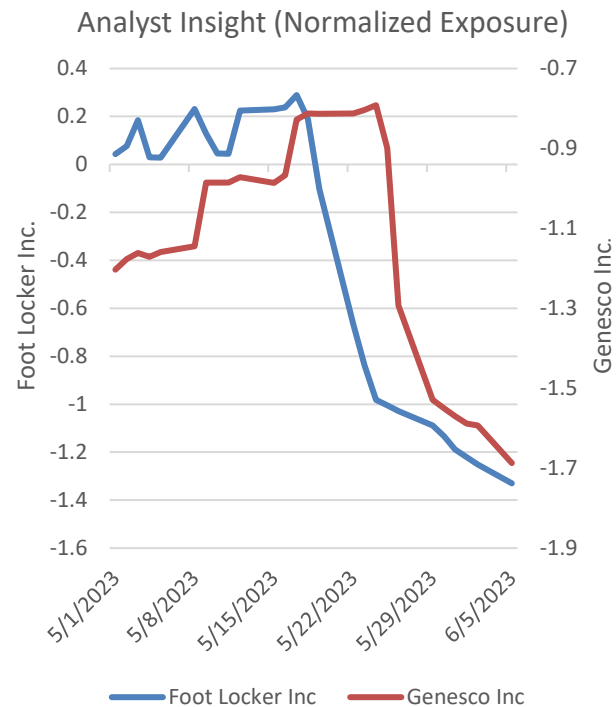


Risk Adjusted Signal



USING PEER GROUP COMPARISON IN THE INVESTMENT DECISION: ENHANCING ANALYST INSIGHT THROUGH PEER ANALYSIS

CAPTURES LAG EFFECTS IN ANALYST REVISIONS



Footlocker:

- Earnings call on 5/19
- Slash guidance, 'consumer softness'

Genesco:

- Earnings call 5/25
- Slash guidance, low consumer demand

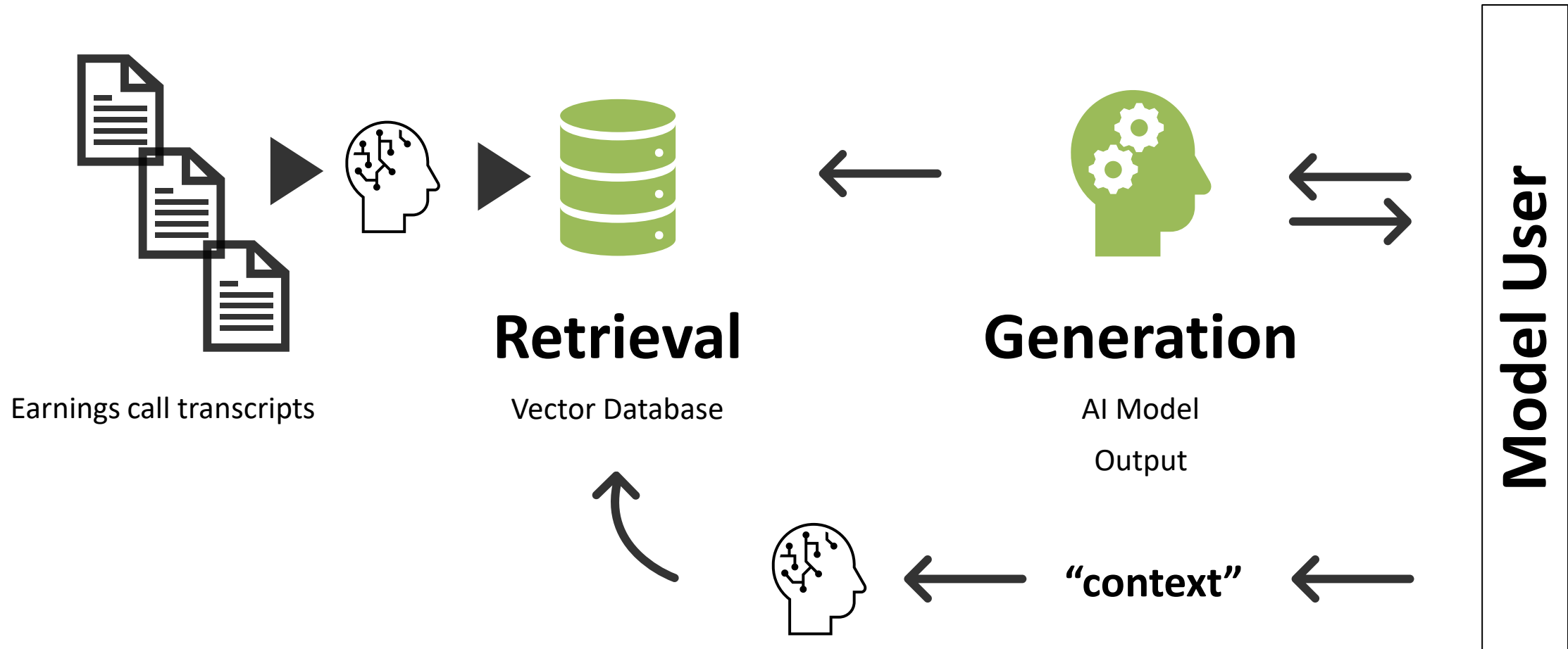


GAINING FURTHER INSIGHTS FROM TEXT DATA: APPLICATIONS OF LARGE LANGUAGE MODELS

- Large Language Models (LLMs) are deep learning algorithms that understand context and meaning to both consume and generate content:¹ Such models are able to:
 - Recognize and understand “human” queries
 - Translate documents
 - Summarize documents
 - Generate content given natural language inputs
- LLMs give the investment practitioner the opportunity to query the “unstructured” data set
- In combination with other data as “context”, LLMs may provide the practitioner with detailed information that can be used to benefit the investment process



RETRIEVAL AUGMENTED GENERATION (RAG)



- Such models can be used to perform “tasks”. E.g – quantify management’s assessment of past performance, expected future performance, and market environment



RETRIEVAL AUGMENTED GENERATION (RAG)

- Consider quantifying management’s assessment of past performance, expected future performance, and market environment
- History of documents used in this example from 02/2017 to 08/2024 with quarterly frequency for a large cap US opportunity set

Context Phrase: “Earnings, Sales, Revenue, EBITDA, Cost, EBIT, Market, Business Environment, Future Growth

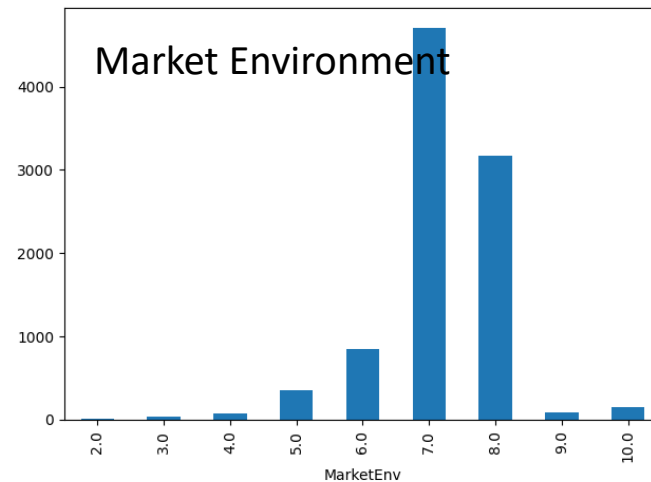
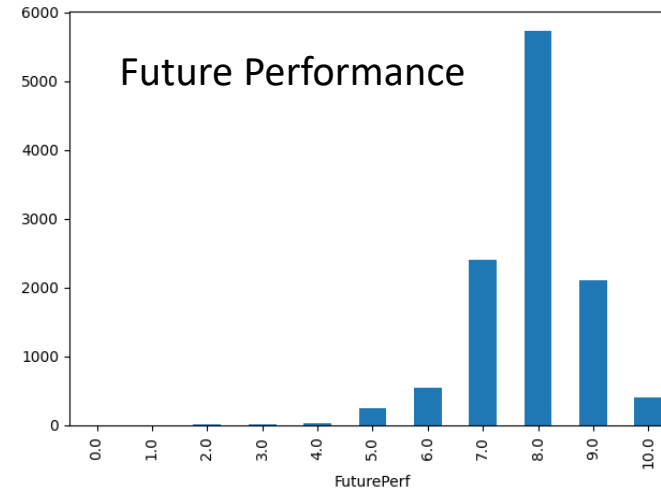
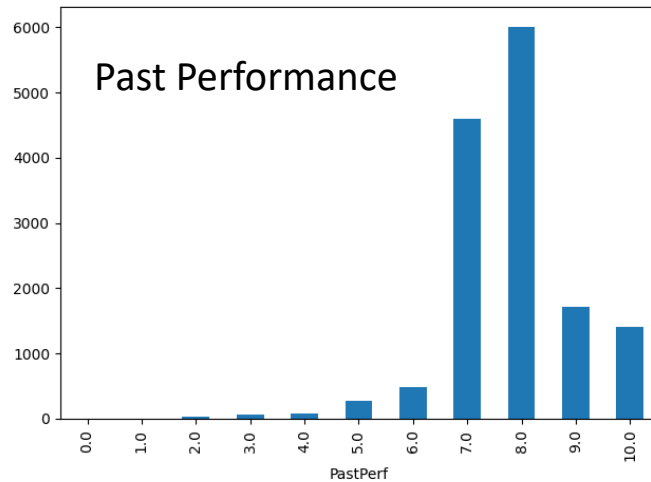
	Type	Description
Past Performance	Integer	How are the firm's past sales and earnings? Scale from 0 to 10, with 0 being very bad and well below expectation and 10 very good and well above expectation. Answer 'NA' if unknown
Future Performance	Integer	How are the firm's expected sales and earnings in the future? Scale from 0 to 10, with 0 being very bad and well below current level and 10 very good and well above current level. Answer 'NA' if unknown.
Market Environment	Integer	How is the current market environment for the firm? Scale from 0 and 10, with 0 being very bad and 10 being very good.



RETRIEVAL AUGMENTED GENERATION (RAG)

- The output is a score between 0 (bad) and 10 (good) showing assessment of the three queries

Total Number of Observations



- The score is a numeric representation of management sentiment
- Many different “questions” can be asked of the RAG model to query the unstructured data

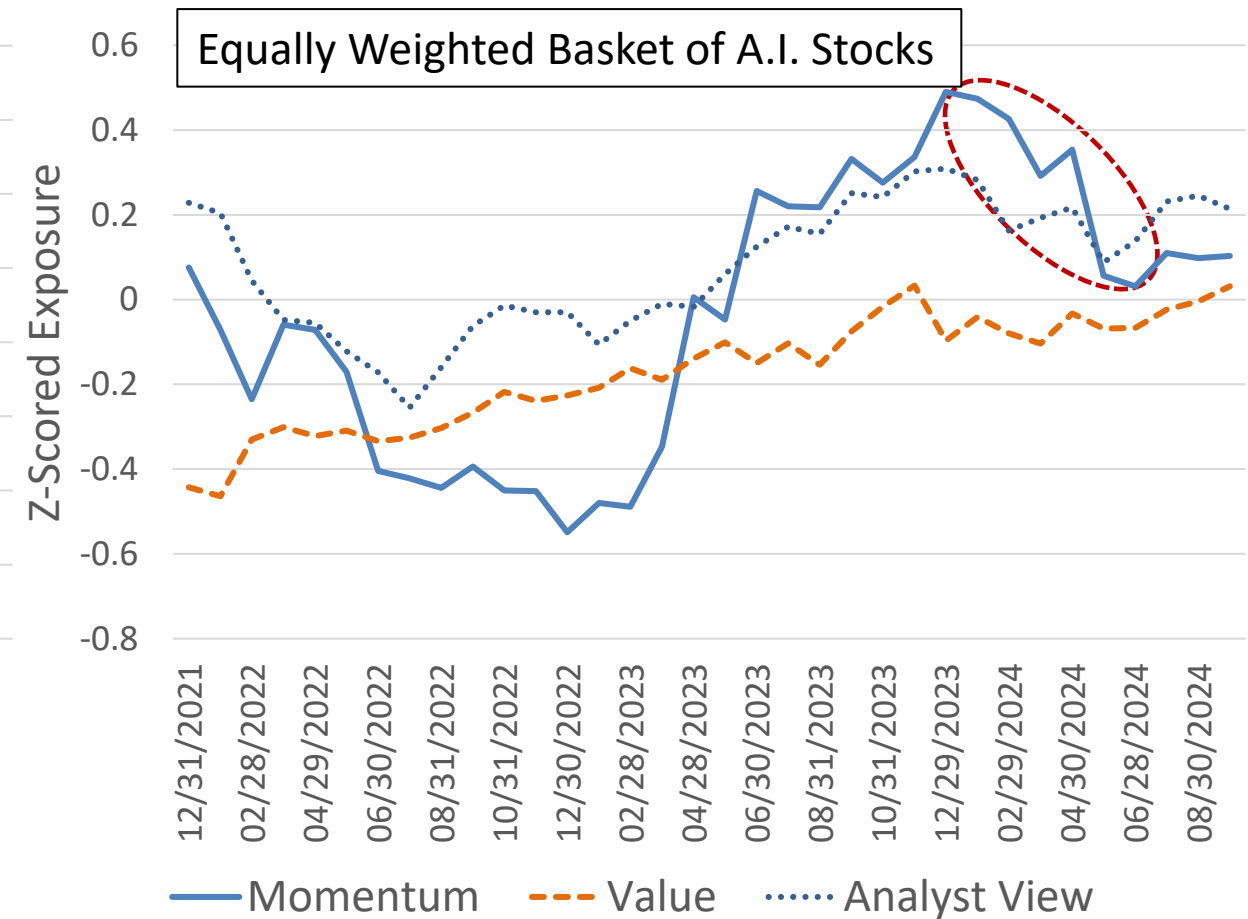
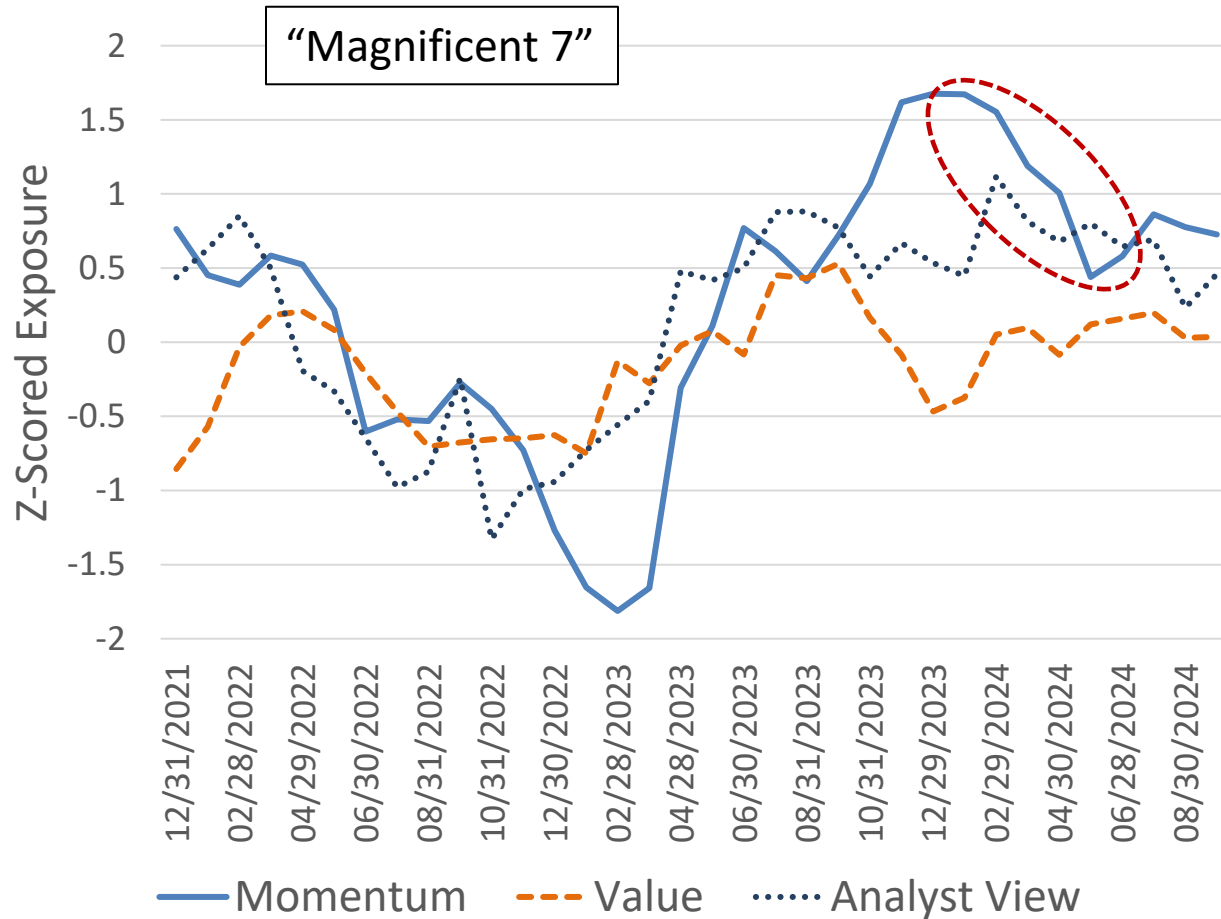


THREE CONSIDERATIONS FOR THE APPLICATION OF NEW TECHNOLOGIES IN THE INVESTMENT PROCESS

1. The investment problem remains the same (and equally difficult!)
 - *Managers are still looking for good companies that stand out from peers*
2. New technologies face some challenges when addressing the investment problem:
 - *It is useful to employ high signal to noise ratio data and combine machine output with traditional metrics and views*
3. When carefully applied, new technologies can lead to refined investment research and greater efficiency in the discovery of new investment ideas
 - *Practitioners can develop refined investment signals and uncover nuanced information by querying large unstructured data sets – **and it can all be done at scale over thousands of securities***



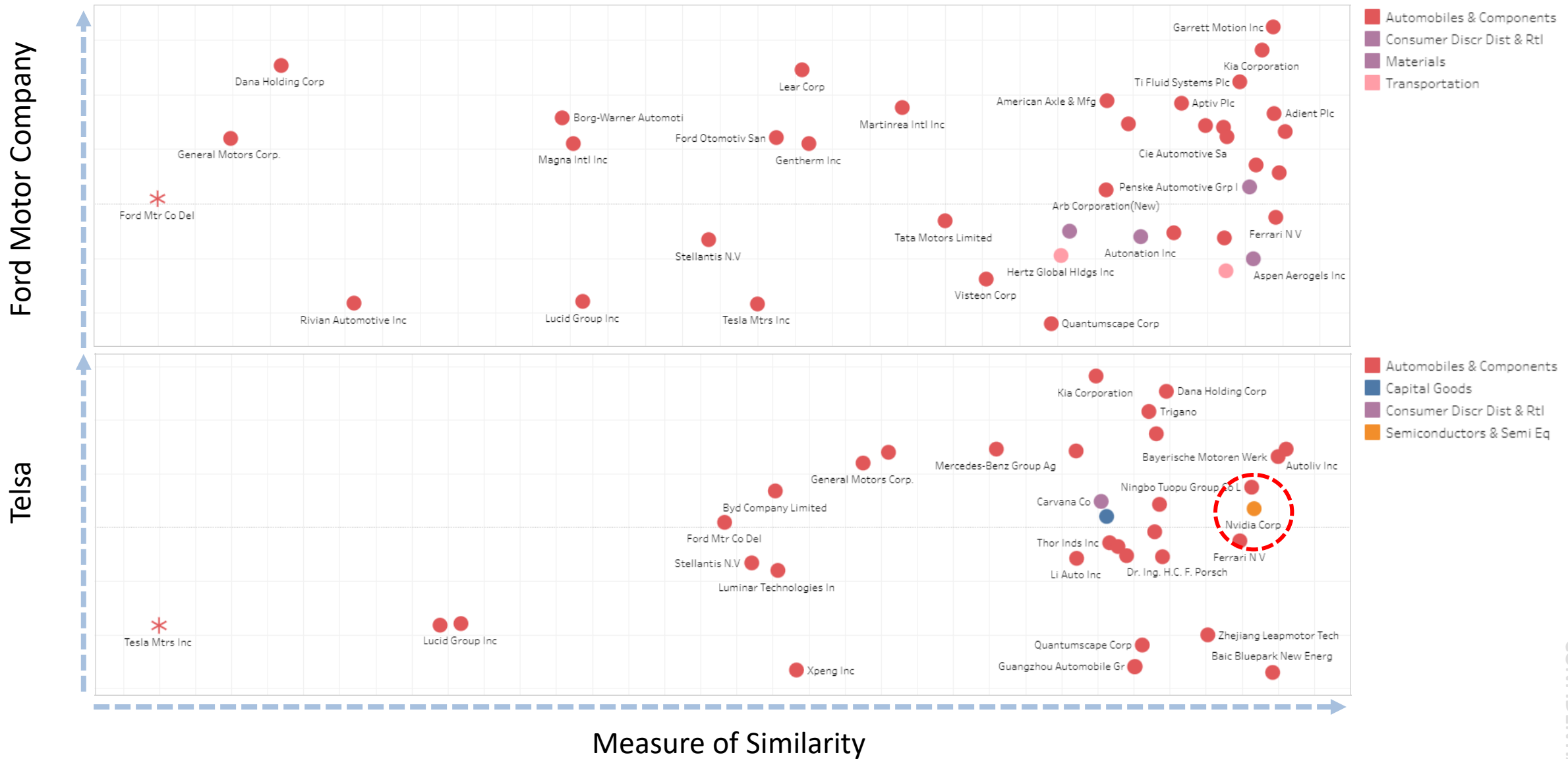
INVESTING IN TECHNOLOGY AS A THEME



- The uncertainty in future cash flows associated with new technology and A. I. models may make it difficult to understand the A. I. theme using traditional metrics



INVESTING IN TECHNOLOGY AS A THEME





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