

# Factor investing

Some thoughts on the factor investing literature  
from the past decade

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# General disclaimers

- When it comes to factor investing, **nobody can agree on anything**, from definitions, to how to (best) do it, etc.
- This presentation contains **my views**.
  - Feel free to disagree. Also please present your views at a future meeting.
  - Factor investing is a hot topic, and everybody would like to hear your views!
- Reducing 10 years of research into a couple of slides **inevitably loses a lot of nuance and subtlety** and **leaves a lot out altogether**.
- Presentations like this are often prefaced with a disclaimer that it isn't investment advice. There's no such disclaimer here!

# A note on terminology

- In most of the literature [typically, nobody can agree on anything]:

**“Factors” = “anomalies” = “smart beta” = “style investing”**

- **Basilico and Johnsen (2019)**: “We will use terms like smart beta, strategic beta, risk premia investing, style investing and **factor investing** interchangeably.”
- This presentation sticks with “factors” and “factor investing”.
  - If this presentation wants to quote a paper that says:

***“Smart beta investing is great”***

This quote will appear in this presentation as:

***“[Factor] investing is great”***

- **Note**: Basically all the research mentioned here is based on the **US market**.

# Overview of talk

- ❑ Reminder: Beating the market (long-term, consistently) is hard.
- ❑ Factors and factor investing. Long-short vs. long-only.
- ❑ Beware of the transaction costs.
- ❑ Identifying factors. Data mining (p-hacking).
- ❑ Constructing factor models. Model mining.
- ❑ Machine learning (ML) is not helping, despite the hype.
- ❑ Factor timing. Predicting the future, and all that.
- ❑ Factor performance: Past is not prologue.
- ❑ How to profit reliably from factor investing.
- ❑ Reminder: Beating the market is hard.

# Reminder: Beating the market is hard

- **Cochrane (1999):**

- “I emphasize a cautionary fact: **The average investor must hold the market.**”
- “You should only vary from a passive market index **if you are different from everyone else.**”
- “It **cannot be the case** that **every investor** should tilt his portfolio toward **value** or other high-yield strategies. If everybody did it, the phenomenon would disappear.”

- **Melas (2016):**

- “In reality, **market-cap benchmarks** are **extremely difficult** to **outperform** consistently.”

- **White and Haghani (2020):**

- “For factors with plausible risk-based explanations, the authors conclude that **even** in the presence of **significant factor premia**, the **market portfolio** is still likely to be **optimal for most investors.**”

- **Nes (2020):** Looking at factor investing ETFs over Jan-2007 and Mar-2020.

- “This thesis does **not find** any statistically significant evidence of [factor] ETFs **outperforming ... broad, cap-weighted market indices.**”

# Preview: What a decade it has been

- Stage 1: Promises, promises
  - **Ang (2014)**: “...there is a **long-run reward** for being exposed to factor risk.”
  - **Amenc et al. (2015)**: “[Factor investing] strategies are usually **marketed** on the basis of **outperformance**.”
  - **UBS (2016)**: “The premise of factor investing... is that stocks with certain characteristics known as 'factors' **outperform the market in the long term**.”
- Stage 2: Excitement, hype
  - **Cerniglia and Fabozzi (2018)**: “factors have become an **increasing fashionable** way to invest assets”
  - **Dopfel and Lester (2018)**: “**extraordinary growth** in the use of [factor investing] funds by institutional investors, both large and small.”
  - **Li et al. (2019)**: “**Assets** have been **flowing steadily** from actively managed funds to **factor-investing strategies** since about 2008.”
- Stage 3: Disappointments, suspicions, recriminations
  - **Arnott et al. (2019)**: “Factor investing has **failed to live up to its many promises**.”
  - **Vincent et al. (2018)**: “Skeptics have stated that the [factor investing] strategies are **merely smart marketing** without any value being added for investors.

# Background: Why factors?

- Example: Plot of share prices over the last year of BHP (= mining company) and CBA (= bank).
  - Different companies, in different industries, with different customers, and different global exposure etc.
  - *Returns* appear to be linked in some way, especially over some periods.



# Background: Why factors?

- Factor argument:
  - BHP and CBA are both exposed to the same underlying, non-industry-specific **factors**.
  - Instead of name/industry diversification, we should be more concerned with the underlying **factor exposure and factor diversification** of our portfolio.





# Factors and Factor Investing

- **Soupé et al. (2019):**
  - “**Factors** are **characteristics** that **explain...** equity portfolio returns.”
- **Briere and Szafarz (2016):**
  - “**Factor investing** emerged as the **byproduct** of **factor models** of asset pricing.”
  - Factor investing “consists in **holding assets** with **positive exposure** to **selected risk factors** and, if possible, shorting those with negative exposure.”

# What is a factor model?

- **Factor model:** A model explaining returns of stocks as a function of multiple *factors*.
- Linear factor models: Most popular.
  - Combination of factors easily understood.
  - Straightforward estimation using time series regression.

Return on stock  $i$       Risk-free rate      Factor returns

$$R_i(t) = r_f(t) + \beta_{i,1} \cdot \underbrace{\begin{bmatrix} F_1(t) \end{bmatrix}}_{\text{Factor 1}} + \beta_{i,2} \cdot \underbrace{\begin{bmatrix} F_2(t) \end{bmatrix}}_{\text{Factor 2}} + \dots + \beta_{i,n} \cdot \underbrace{\begin{bmatrix} F_n(t) \end{bmatrix}}_{\text{Factor } n}$$

- Nonlinear factor models:
  - Nonlinear model (e.g. neural network) and/or complicated factors.
  - Difficult to understand or explain factors and/or model implications.

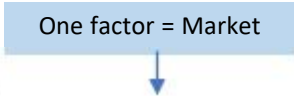
E.g. neural network

Return on stock  $i$       Feature vector


$$R_i(t) = f(\mathbf{X}(t))$$

# Some classical linear factor models

- CAPM (1-factor):


$$R_i(t) = r_f(t) + \beta_{i,1} \cdot \left[ \underbrace{F_1(t)}_{\text{Market risk premium}} \right]$$
$$= r_f(t) + \beta_{i,1} \cdot [R_M(t) - r_f(t)]$$

- Fama/French 3 factor model (FF3):
  - Size factor = SMB = Small *minus* Big:
  - Value factor = HML = High *minus* Low:


$$R_i(t) = r_f(t) + \beta_{i,1} \cdot \left[ \underbrace{R_M(t) - r_f(t)}_{\text{Market risk premium}} \right] + \beta_{i,2} \cdot \left[ \underbrace{SMB(t)}_{\text{Size factor}} \right] + \beta_{i,3} \cdot \left[ \underbrace{HML(t)}_{\text{Value factor}} \right]$$

# Asset allocation vs. factor allocation

- Suppose we have the following:
  - $n$  factors in a linear factor model (zero risk-free rate).

Return on stock  $i$

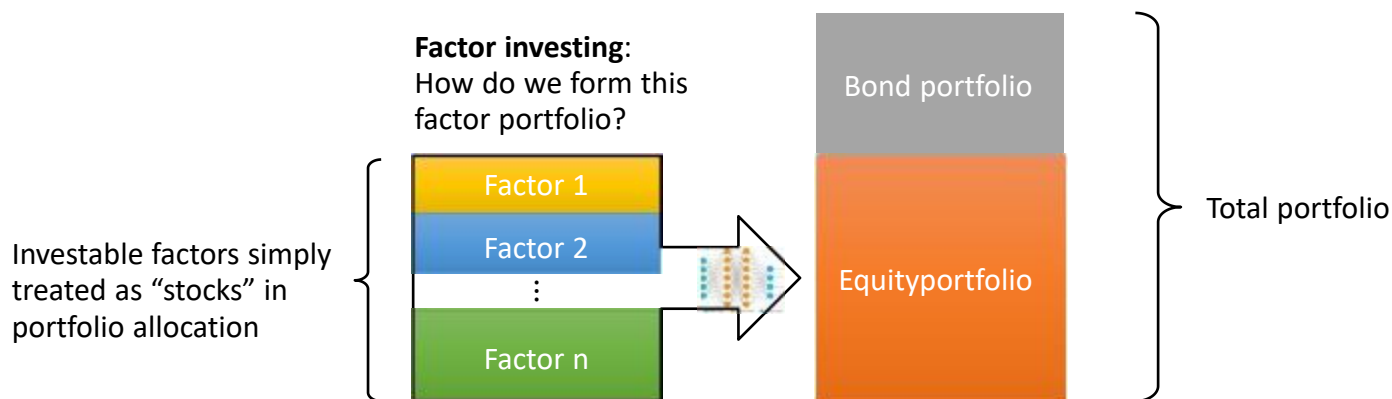
$$\boxed{R_i(t)} = \beta_{i,1} \cdot \underbrace{\begin{bmatrix} F_1(t) \end{bmatrix}}_{\text{Factor 1}} + \beta_{i,2} \cdot \underbrace{\begin{bmatrix} F_2(t) \end{bmatrix}}_{\text{Factor 2}} + \dots + \beta_{i,n} \cdot \underbrace{\begin{bmatrix} F_n(t) \end{bmatrix}}_{\text{Factor } n}$$

- $N$  stocks with returns  $\{R_i : i = 1, \dots, N\}$
- Form portfolio  $p$  with asset allocation/weights  $\{w_i : i = 1, \dots, N\}$
- Portfolio return:

$$\begin{aligned}
 R_p(t) &= \sum_{i=1}^N w_i \cdot \boxed{R_i(t)} \quad \leftarrow \text{Linear factor model} \\
 &= \sum_{i=1}^N w_i \cdot \boxed{\beta_{i,1} F_1(t) + \beta_{i,2} F_2(t) + \dots + \beta_{i,n} F_n(t)} \\
 &= \underbrace{\left( \sum_{i=1}^N w_i \beta_{i,1} \right)}_{\hat{w}_1} \cdot F_1(t) + \underbrace{\left( \sum_{i=1}^N w_i \beta_{i,2} \right)}_{\hat{w}_2} \cdot F_2(t) \dots + \underbrace{\left( \sum_{i=1}^N w_i \beta_{i,n} \right)}_{\hat{w}_n} \cdot F_n(t) \\
 &= \sum_{j=1}^n \hat{w}_j \cdot F_j(t)
 \end{aligned}$$

# Summary: Factor investing

- *What is factor investing?*
  - Forming an equity portfolio by **increasing or decreasing exposures to particular investable factors**.
  - This (factor) equity portfolio is then combined with a bond portfolio to get the total investment portfolio.



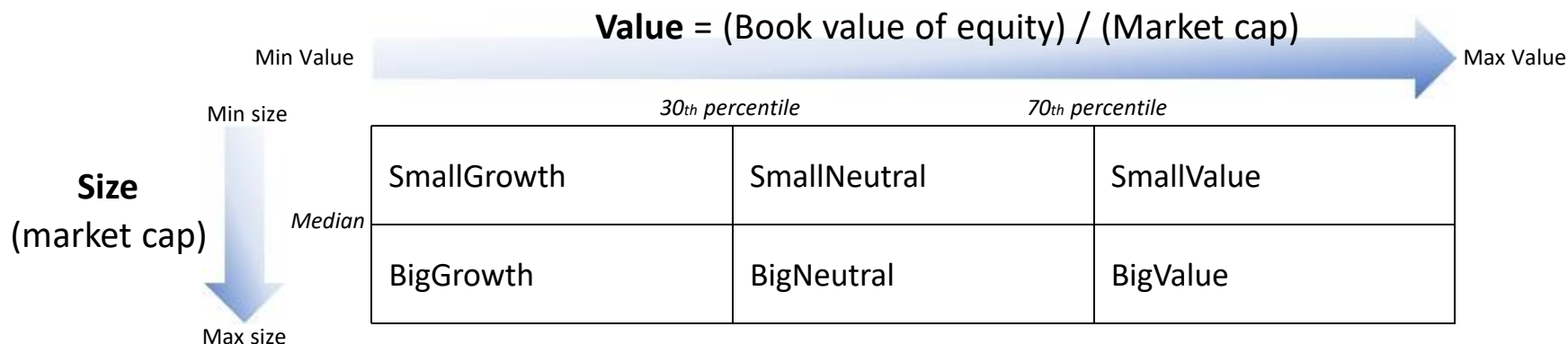
- *Why factor investing?*
  - Reduces equity portfolio allocation decision to only  **$n$  factors**, instead of  $N$  stocks, with  $n \ll N$ .
  - Relatively easy to interpret the resulting allocation as an **investment style** (e.g. “value” investing and “momentum/trend-following” strategy etc.)
  - Arguably some **theoretical justification** for using factors, and by implication, for factor investing.

# Investable factors as “stocks”

- Is it reasonable for a retail investor to treat investable factors as “stocks”?
  - Depends on what we mean by factors.
- Reminder:
  - The term “**factor**” is used here to denote *any* portfolio formed to highlight a particular characteristic of the underlying stocks.
- Distinguish two classes of factors:
  1. **Academic (long-short) factors:** technical definition of the factor as used in a factor model.
  2. **Long-only factors (“factor tilt”):** How the conclusions of factor model theory appear to be mostly used in practice.

# Academic (long-short) factors

- Example: Size and Value factors in FF3 .
  - FF sorts firms by “Value” and “Size” information, identify **6 groups** of stocks.



- Form a market cap-weighted portfolio of each group.
- Construct **long-short factors** using **returns** of these portfolios:

<b>SIZE factor</b>	$SMB = \frac{1}{3} (Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3} (Big\ Value + Big\ Neutral + Big\ Growth)$
<b>Value factor</b>	$HML = \frac{1}{2} (Small\ Value + Big\ Value) - \frac{1}{2} (Small\ Growth + Big\ Growth)$

# Academic (long-short) factors

- From an academic factor model perspective, a factor needs to capture some “*extra* dimension of risk”, unaccounted for by other factors. As a result, it is typically:
  1. Long-short.
  2. Zero beta with respect to other factors (including market factor).
- In practice, academic factors portfolios may be **expensive** and/or **difficult/impossible** to implement and maintain.
- **Bender et al. (2013):**
  - “The original studies on factors were intended to identify which stock characteristics **explained returns**.”
  - “These studies were **not concerned** with **whether those factors** were actually **investable**.”
  - “Specifically, the factor portfolios constructed by the academics in these studies were **not designed** for **actual implementation**.”
- **Novy-Marx and Velikov (2016):**
  - Show that “**almost no factor**, constructed as a **long-short portfolio**, with turnover exceeding 50% has **any return left** after **accounting for transactions costs**.”
- **Arnott et al. (2017c):**
  - “We find **slippage** between the factor returns realized by mutual fund managers and the theoretical factor returns earned by **long-short paper portfolios**”
  - “The **source** of the slippage appears to be **costs related to implementation**...”

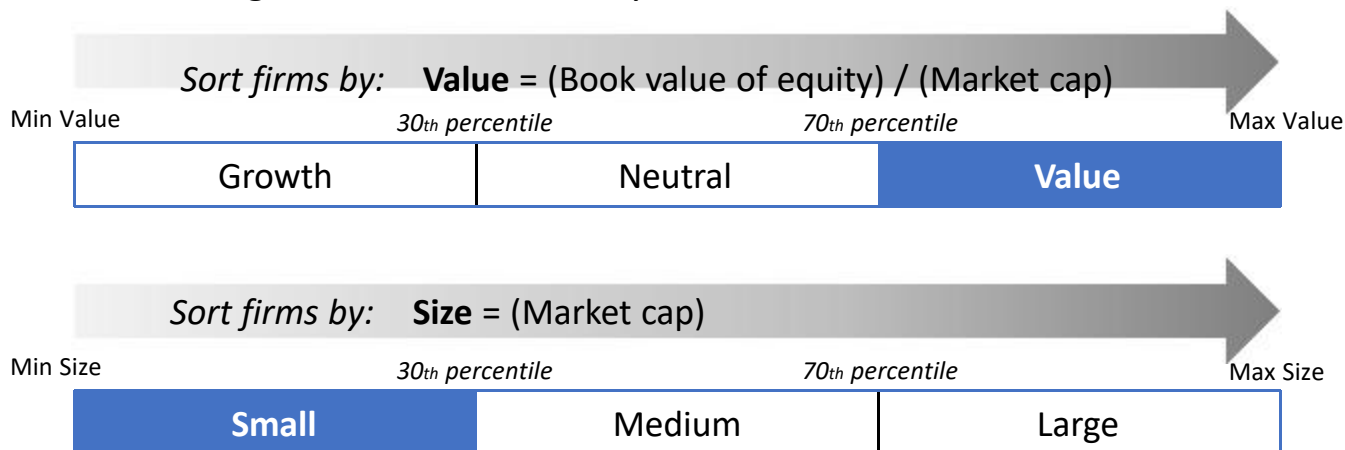


# Academic (long-short) factors

- The good news: We can drop the “short” leg of the academic factors and still get some benefit from factor investing.
- **Israel and Moskowitz (2013):**
  - “Factor investing can work even with no short-selling.”
- **Blitz et al. (2014)** investigates whether “factor investing can best be implemented using a long-only or a long-short approach.”
  - “We show that **implementation costs** [transaction costs, borrowing costs, margin requirements] ... may **completely offset** the **value added** of a **long-short implementation**.”
- **Blitz et al. (2020a)** examines “the **long** and **short sides** of Fama-French factor portfolios and found that the **added value** of common factors is **generally concentrated** in the **long legs**”.
  - Also, “long legs offer more diversification than the short legs”
  - “Short selling also entails additional risks, such as (1) the potential for unlimited losses, (2) short squeeze scenarios...(3) counterparty risk, and (4) reputational risk.”
- Unfortunately, a lot of academic research ignore these issues, and still construct long-short factor portfolios with some enthusiasm. (e.g. **Lioui and Tarelli (2020)**)

# Long-only factors (factor tilts)

- **Cazalet and Roncalli (2014):** “Most *products* [e.g. investable ETFs etc.] based on **risk factors** generally use a **long-only portfolio**.”
- Use **long-only “factors”** (factor tilts) to gain exposure to the conclusions of factor theory.
- ~~Example:~~ Some rough, informal implications of FF3:
  1. *small* stocks tend to outperform *large* stocks.
  2. *value* stocks tend to outperform *growth* (low value) stocks.
- To take advantage of this, sort firms by “Value” and “Size”:



- In our portfolio, we might **assign relatively larger weights** to “**Value**” stock index and “**Small**” stock index.
- Factor tilts.



# Long-only factors (factor tilts)

- A lot of recent research do recognize the fact that many investors are limited to **long-only, investable** factor portfolios.
- Some recent examples:
  - **Ghayur et al. (2018)** considers “**long-only** multifactor strategies...”
  - **Soupé et al. (2019)**:
    - Construct a “**long-only** constrained portfolio that retains the targeted exposures to four factors.”
  - **Du and Price (2018)**:
    - “We focus on **long-only** investing because most mutual funds and ETFs are long-only and individual investors may be more comfortable with long-only portfolios.”
  - **Hjulgren (2018)**:
    - “Despite these drawbacks, factor ETFs have offered **higher returns** and Sharpe ratios than their respective **long-short counterparts**, which gives **support for the long-only approach** to factor investing.”
  - **Hansen and Bonne-Kristiansen (2020)**:
    - “Both the **implementability** and **profitability** of the strategies investigated by this thesis are immensely impacted by the type and size of the investor.”
  - **Feng and He (2020)** explicitly considers long-only factor investing.
    - “We optimize the mean-variance utility and update portfolio weights every month, with constraints of **long-only** and no leverage.”

# Beware of the Transaction Costs


- We distinguish between 2 types of transaction costs:
  - **Implicit transaction costs:** Market impact of large factor ETFs rebalancing.
  - **Explicit transaction costs:** Direct cost of trading, e.g. proportional transaction costs.
- Focusing on **explicit transaction costs**, something to keep in mind when reading about fantastic **long-only or long-short** factor investing results in the literature:
  - **Cerniglia and Fabozzi (2018):**
    - “Many studies on [factor investing] **ignore the costs** associated with trading, thereby **overstating the returns these strategies achieve.**”
  - **Li and Shim (2019):**
    - “In this study, we highlight the **trade-off** between **gaining excess returns** associated with factors and the impact of **implementation costs** in constructing a multi-factor [factor investing] strategy.”
  - **Dichtl et al. (2019):**
    - Find that “**active [long-only] factor allocation outperforms** the 1/N benchmark **by only seven basis points after transaction costs** with the net return erosion stemming from excessive trading frequency as warned as a potential pitfall by various sceptics.”

# Overview of talk

- ☒ Reminder: Beating the market (long-term, consistently) is hard.
- ☒ Factors and factor investing. Long-short vs. long-only.
- ☒ Beware of the transaction costs.
- ☐ Identifying factors. Data mining (p-hacking).
- ☐ Constructing factor models. Model mining.
- ☐ Machine learning (ML) is not helping, despite the hype.
- ☐ Factor timing. Predicting the future, and all that.
- ☐ Factor performance: Past is not prologue.
- ☐ How to profit reliably from factor investing.
- ☐ Reminder: Beating the market is hard.


# Explaining factor models

- Consider the Fama/French 3 factor model (FF3):

$$R_i(t) = r_f(t) + \beta_{i,1} \cdot \underbrace{\left[ \frac{R_M(t) - r_f(t)}{\text{Market risk premium}} \right]}_{\text{Market risk premium}} + \beta_{i,2} \cdot \underbrace{\left[ \frac{SMB(t)}{\text{Size factor}} \right]}_{\text{Size factor}} + \beta_{i,3} \cdot \underbrace{\left[ \frac{HML(t)}{\text{Value factor}} \right]}_{\text{Value factor}}$$


Three factors: Market, Size, Value

- The intercept (**risk-free rate**) and **market risk premium** makes intuitive sense:
  - But why **two** additional factors?
  - And why should the two additional factors be **Size and Value**, specifically?

$$R_i(t) = r_f(t) + \beta_{i,1} \cdot \underbrace{\left[ \frac{R_M(t) - r_f(t)}{\text{Market risk premium}} \right]}_{\text{Market risk premium}} + \beta_{i,2} \cdot \underbrace{\left[ \frac{SMB(t)}{\text{Size factor}} \right]}_{\text{Size factor}} + \beta_{i,3} \cdot \underbrace{\left[ \frac{HML(t)}{\text{Value factor}} \right]}_{\text{Value factor}}$$


# Some thoughts on explanations

- Suppose I make the following claim:

“When the stock market crashes, (US) Treasury bonds do well.”

- How would you go about **explaining** this claim?



- **Argument group 1: Institutional mandates and the resulting actions, policies.**

Example: US Fed actions relating to interest rates, market stability, liquidity, etc.



- **Argument group 2: Behavioral and/or economic arguments.**

Example: “flight to quality”, “increased risk aversion”, “safe havens”



- **Argument group 3: Purely empirical observations.**

Example: “Look at the history, it just always works out that way.”

# Factors: Non-explanations vs. explanations

- Suppose I make the following claim [basically interpreted as “investment advice” by normal people, despite all those disclaimers]:

Example: “There is such a thing as the **size premium**: Small stocks tend to outperform large stocks.”

- How would you go about **explaining** this claim?

- **Argument group 1: Institutional mandates and the resulting actions, policies.**

- Missing when it comes to factors!
- Some people have tried, but arguing vaguely about incentives of pension funds is just awkward.

- **Argument group 2: Behavioral and/or economic arguments.**

- Also mostly missing when it comes to factors!
- It is too easy to come up with some semi-plausible, realistic sounding explanations [hint: use big words, include the word “rational” at least once], but how sound are these arguments, actually? How much of it is fancy hand-waving?



- Some exceptions: E.g. “momentum” and “irrational exuberance”.

- **Argument group 3: Purely empirical observations.**

- We are down to this: “Look at the history, it seems to work out that way over long periods. Just look at the t-statistics!”
- But this ignores the problem of widespread data mining / p-hacking.



# Factors: Non-explanations vs. explanations

- **Fischer Black (1992):**

- “Fama and French... **give no reasons** for a **relation** between **size** and **expected return**.”
- “...I think it is quite possible that even the book-to-market [**value**] effect **results from data mining**, and will **vanish in the future**.”
- “**Lack of theory is a tipoff: watch out for data mining!**”

- **Lioui and Poncet (2011):**

- “These factors [Size and Value], however, are based on **purely empirical considerations, lack theoretical underpinnings**, and are built in a rather **arbitrary manner**.”
- “In particular, their **economic links** to **systematic risk** are **not clear**.”
- “The alleged ability of innovations in predictors to explain the cross section of expected excess returns is **rather illusory**.”

- **Arnott et al. (2019):**

- “We detail the **impact of data mining** on both factor selection and **disappointing out-of-sample factor performance**.”

- Also, nobody cares. As **Taylor Swift (2014)** pointed out, though not in the context of factor investing, “...the haters gonna hate, hate, hate, hate, hate.”

# Identifying factors

- It really is the discovery of the Goose that Laid the Golden Eggs:
  - Lots and lots of factors have been identified (>400).
  - Think of all the papers, PhDs, postdoc jobs, etc.
- **Cochrane (2011)** first coined the term “**zoo of new factors**”.
  - Everybody calls it a “factor zoo” these days.
- **Harvey and Liu (2020)**:
  - “The finance profession has been on a **50-year quest to identify factors** that explain the cross- section of expected returns.”
  - “However, even after all this time, there is **no consensus** as to what the factor structure looks like.”
- **Hsu et al. (2015)**:
  - “In our view, a **robust factor** is, first, one whose **economic underpinnings** and persistence have been **debated** and **validated** in **numerous research papers**”
- So **about those “numerous research papers”** that “debated” and “validated” the “economic underpinnings” etc. of the factors:
  - Things have not ... shall we say ... gone well.

# Identifying factors

## Replicating Anomalies

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June 2017 §

### Abstract

The anomalies literature is infested with widespread p-hacking. We replicate this literature by compiling a large data library with 447 anomalies. With microcaps alleviated via NYSE breakpoints and value-weighted returns, 286 anomalies (64%) including 95 out of 102 liquidity variables (93%) are insignificant at the 5% level. Imposing the  $t$ -cutoff of three raises the number of insignificance to 380 (85%). Even for the 161 significant anomalies, their magnitudes are often much lower than originally reported. Among the 161, the  $q$ -factor model leaves 115 alphas insignificant (150 with  $t < 3$ ). In all, capital markets are more efficient than previously recognized.

Hou et al. (2020): [working paper]

**“The [factor] literature is infested with widespread p-hacking.”**

Hou et al. (2020): [published version]

**“Most [factors] fail to hold up to currently acceptable standards for empirical finance.”**

## The Review of Financial Studies



## Replicating Anomalies

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Most anomalies fail to hold up to currently acceptable standards for empirical finance. With microcaps mitigated via NYSE breakpoints and value-weighted returns, 65% of the 452 anomalies in our extensive data library, including 96% of the trading frictions category, cannot clear the *single* test hurdle of the absolute  $t$ -value of 1.96. Imposing the higher multiple test hurdle of 2.78 at the 5% significance level raises the failure rate to 82%. Even for replicated anomalies, their economic magnitudes are much smaller than originally reported. In all, capital markets are more efficient than previously recognized. (JEL C58, G12, G14, G17, M41)

# Identifying factors

- **Harvey et al. (2016):**

- Test **316 factors** that claim to explain the cross-section of expected returns.
- “Given the plethora of factors, and the inevitable data mining, many of the historically discovered factors would be deemed ‘significant’ by chance.”
- “We argue that **most claimed research findings** in financialeconomics are **likely false.**”
- “Many of these factors that our method deems **statistically true** have **tiny Sharpe ratios.**”

- **Hou et al. (2020):**

- “Most [of the **452 factors** tested] fail to hold up to currently acceptable standards for empirical finance.”
- “Even for replicated [factors], their **economic magnitudes** are much **smaller** than **originally reported.**”

- **Feng et al. (2020):**

- “Our factor library contains **99 risk factors.**”
- “**Many factors** introduced in the last few years appear **entirely redundant** and contain **no new useful information** for pricing the cross section of returns.”

# Which factor model?

- It isn't just individual factors...what about factor models? I.e. what combination of factors should we prefer?
- Some famous examples:
  - **Fama and French (1992)**: 3 factor model
  - **Carhart (1997)**: 4 factor model
  - **Fama and French (2015)**: 5 factor model
  - **MSCI Barra factor model ( $\geq 1996$ )**: >40 factors
- **Harvey and Liu (2020)**:
  - “it is **hard to interpret the literature** when:
    - “one set of authors presents evidence in favor of **their five-factor** model with one set of portfolios and”
    - “another set of authors presents evidence in favor of **their five-factor** model based on a different set of portfolios.”

# Which factor model?

- **Kogan and Tian (2015)**: empirical investigation of “model-mining”:
  - “**How** should we **evaluate proposed factor pricing models** with strong pricing performance but **without sound theoretical motivation?**”
  - “We quantify just **how easy** it is to **generate** seemingly **successful empirical c-factor models.**” [ $c$  = number of factors]

## Step 1: 27 firm characteristics [factors]

proposed in the literature as predictive variables for stock returns



## Step 2: Randomly select $X$ number of factors



## Step 3: Fit a $(X+1)$ -factor linear factor model

$$R_i(t) = r_f(t) + \beta_{i,1} \cdot \underbrace{\left[ R_M(t) - r_f(t) \right]}_{\text{Market risk premium}} + \beta_{i,2} \cdot \text{red bead} + \beta_{i,3} \cdot \text{green bead}$$

## Step 4: Evaluate performance of random factor model

“The bottom line is that over the 1971-2011 sample period, many **randomly constructed** empirical **three-factor models** comfortably ‘outperform’ both the CAPM and the Fama-French model.”

# ML: Model/data mining

- Machine learning (ML): What about recent rise in non-linear factor models?

E.g. neural network

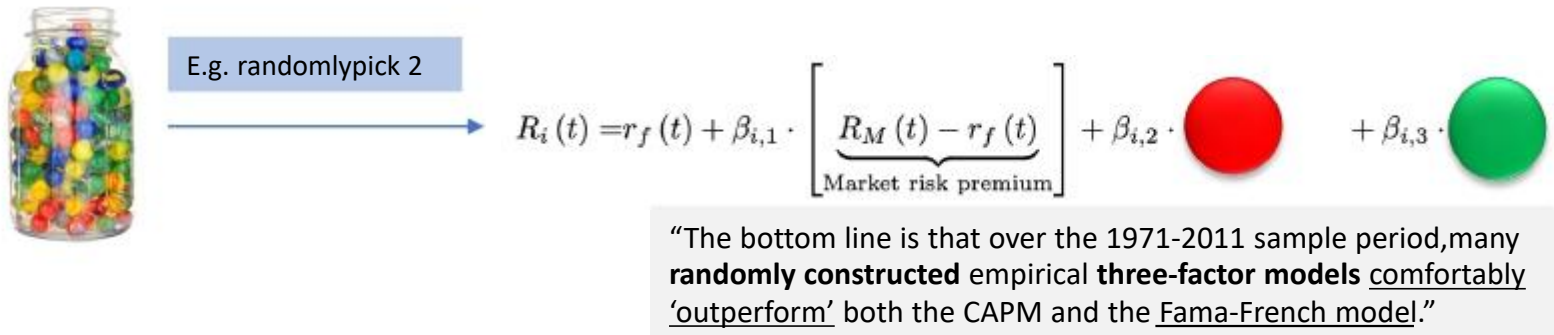
X = Factors (feature vector)

$$R_i(t) = f(\mathbf{X}(t))$$

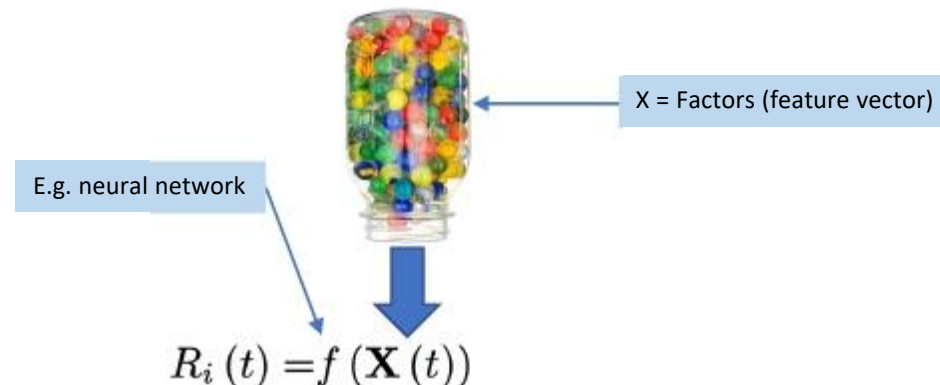
- ML papers, for the most part, have **embraced data mining**, often with an unabashed enthusiasm.
  - In financial economics, there's often at least an *attempt* at trying to come up with an economic rationale for factors.
- But what about that **fantastic out-of-sample ML portfolio performance**?
  - Large number of features considered.**
  - If a feature works well “in-sample” but *not* “out-of-sample”, it is dropped: “overfitting”. We may never know about it!
    - It's not news if the weather in Waterloo fails to predict the stock market.*
  - If a feature works well “in-sample” *and* “out-of-sample”, it is retained: “excellent predictor”.
  - So what's the problem?
    - Harvey and Liu (2020)**, referring to factor models generally: “**given the large number of candidate factors, some could just be lucky.**”
    - In fact, I would say some are all but *guaranteed* to be lucky.

# ML: Model/data mining

- Recall **Kogan and Tian (2015)**: With **linear** factor models, **randomly selected** factor models can easily outperform the classical factor models:



- The ML approach is basically using (i) a **highly non-linear model** (NN) of (ii) **ALL the factors** one can think of....
  - Comparing this result with classical linear factor models.
  - And then be very pleased if it outperforms the linear, classical factor models.





# ML factor models

- **Gu et al. (2020):** [NN]
  - “We conduct a large-scale empirical analysis, investigating nearly **30,000 individual stocks** over 60 years from 1957 to 2016.”
  - “Our predictor set includes **94 characteristics** for *each stock*, **interactions of each characteristic** with **8 aggregate time-series variables**, and **74 industry sector dummy variables**.”
  - “Some of our methods **expand this predictor set much further** by including **nonlinear transformations** and **interactions** of the baseline signals.”
- **Alberg and Lipton (2018):** [NN]
  - “The final list contains **11,815 stocks**.”
  - “For each stock and at each time step  $t$ , we consider a total of **20 input features**.”
  - **16** features based on **financial statement** info, **4** stock price “momentum features”.
- **Chen et al. (2019):** [NN]
  - Considers macroeconomic indicators as features in an asset pricing model.
  - “We collect **178 macroeconomic time series** from three sources.”
  - “Our recurrent Long-Short-Term-Memory network finds a small set of **hidden economic state processes**.”

# ML factor models

- **Cong et al (2020)**: The “AlphaPortfolio” paper.
  - From the paper: “The resulting AlphaPortfolio yields **stellar out-of-sample** performances even after imposing various economic and trading restrictions.”
  - **It’s not pitched as a “factor model”, but on some level, it basically is one.**
    - “Importantly, we use polynomial-feature-sensitivity and textual-factor analysis to ...[do amazing things]. Such ‘economic distillations’ **reveal key market signals, firms’ financials...that drive investment performance.**”
- So which factor (feature) is most prominent in delivering this “stellar out-of-sample” performance?
  - **Inventory change, or IVC**: which shows up *twice(!)* as **IVC** and **(IVC<sup>2</sup>)** in the list of the 15 “most dominant features”.
  - IVC = “**change in inventories** over the **average total assets** of  $t$  and  $(t-1)$ ”:
$$IVC_t = 2 \times \frac{[Inv_t - Inv_{t-1}]}{[Assets_t + Assets_{t-1}]}$$
  - **Is this ratio really a robust predictor of investment performance?**
    - What is the IVC of Facebook or Google or Moderna or Zoom?
    - Is higher IVC better? Is smaller IVC better? Sensitivity of this ratio?
  - In the 61 pages(!) of the AlphaPortfolio paper, the central role of this ratio (and ratio<sup>2</sup>) in achieving “stellar” performance raises **no concerns**.

# ML factor models

- I'm *not* saying IVC contains no information.
  - But if IVC is the *dominant driver of “stellar” predictive performance*, I have questions [given the background of data mining and factors], and it would be nice to see some attempted answers.
- To their credit, **Cong et al (2020)** does try to figure out *which features* explain the resulting portfolio allocation decisions.
  - That is the reason why I know that IVC (and  $IVC^2$ ) is so prominent.
- The most common scenario in ML literature is that authors don't care which features are the most prominent in asset allocation decisions.
  - (or at best there is some rudimentary “sensitivity analysis” or something.)
- When it comes to factor investing, ML is not helping with the widespread data mining / model mining problem.
  - ML just gives everybody the permission *not* to feel guilty about doing it.

# Factors in practice: A matter of convention

- So **which factors** should we consider as the “true factors”?
- In the literature, the **selection of candidate factors** for **factor investing purposes** is basically a **matter of convention**:
  - Some factors are just commonly accepted as factors: **Size, Value, LowVol, Momentum**, and maybe a handful of ill-defined others, like Quality and “Multi-factor”.
  - Whether or not the original “discovery” of a factor suggests it is the result of data mining or not, nobody cares. Conventions rule.
- Examples:
  - **Melas (2016)**: “Factors are **well documented** in academic finance research. The most important equity factors include value, size, momentum, volatility, quality, and yield.”
  - **HSBC (2015)**: “...it is essential to focus only on factors that are **strongly supported by empirical evidence** with **solid economic justifications**. From this perspective the value, size, momentum, low volatility and quality factors seem a natural choice.”
  - **Blitz (2017)** : “...**established factors** such as size, value, momentum, and low volatility”
  - **Fitzgibbons et al. (2017)**: “We focus on value and momentum, two **well-known styles**”
  - **Briere and Szafarz (2017)**: “Working with classic factors (size, value, and momentum) is an advantage, since the **literature is consensual** about their relevance”
  - **Li and Shim (2019)**: “Some of the **most commonly used factors** in investor portfolios are value, momentum, quality, low risk, and size...”
  - **Blitz et al. (2020a)**: “**Evidence** for the existence of various factor premiums in the equity market, such as the value, momentum, and low-risk premiums - **is abundant.**”

# Overview of talk

- ☒ Reminder: Beating the market (long-term, consistently) is hard.
- ☒ Factors and factor investing. Long-short vs. long-only.
- ☒ Beware of the transaction costs.
- ☒ Identifying factors. Data mining (p-hacking).
- ☒ Constructing factor models. Model mining.
- ☒ Machine learning (ML) is not helping, despite the hype.
- ☐ Factor timing. Predicting the future, and all that.
- ☐ Factor performance: Past is not prologue.
- ☐ How to profit reliably from factor investing.
- ☐ Reminder: Beating the market is hard.

# Factor timing

- Finally, we get down to the business of predicting the future.

- “When, **clutching our crystals** and **nervously consulting** our **horoscopes**, our critical faculties in decline, unable to distinguish between what feels good and what's true, **we slide**, almost **without noticing**, **back into superstition and darkness...**”

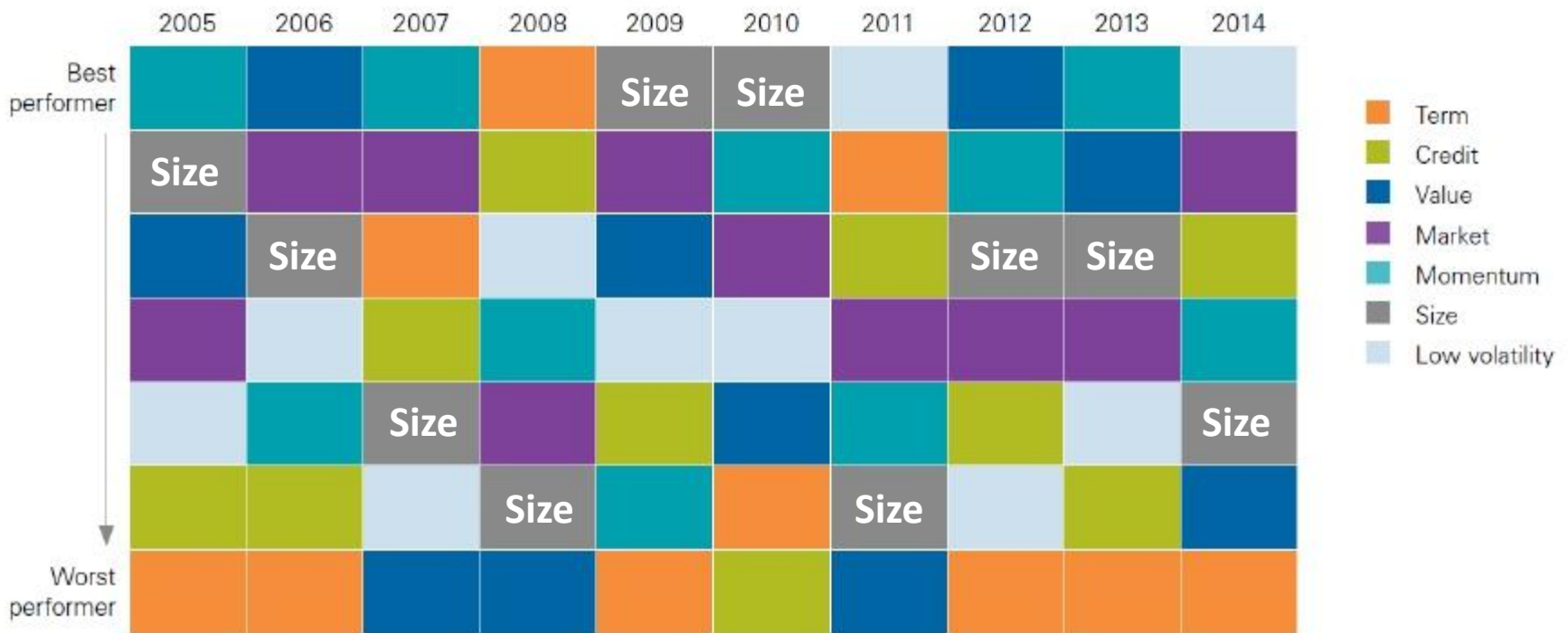
- Carl Sagan, *The Demon-Haunted World: Science as a Candle in the Dark*.

- So let's slide into superstition and darkness...

# Factor timing

- **Vanguard Research (2015):**

- **Ranking of annual returns** of selected **long-only factor portfolios** over 10 years



- Factor timing: Can we somehow **predict which factors** are going to perform well/not so well, **next**?
  - Example, : Can we use information from, say, 2005-2008 to predict its great performance in 2009-2010?

# Factor timing

- Informal observation:
  - There seems to be a **practitioner/academic split** in factor timing literature.
  - “**Practitioners**” = authors affiliated with the wealth management industry.
  - “**Academics**” = authors with university affiliations.
- In summary:
  - “**Practitioners**” are **very, very suspicious** about factor timing.
  - “**Academics**” are **very excited** and report \*amazing\* findings:
    - For some reason, instead of quietly making a fortune, these academic results are inexplicably published in random journals.
- Before giving examples, a couple of things should be noted.

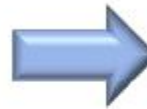


# Factor timing: General comments

- **Asness (2016):**
  - “There is **powerful incentive to oversell timing ability.**”
  - “Factor timing has the potential of reintroducing a type of **skill-based active management** (as timing is generally thought of this way) back into the equation.”
- My translation: If you can convince people of your crystal ball’s predictions, they’ll pay you good money for it.

# Factor timing: General comments

- **Spam email** that I recently received
- The email contains some “interesting” statements:
  - *“i struck Mandelbrot’s cluster effect – 28 stop losses in a row, wiping my portfolio”*
  - *“But predicting the next day’s movement direction (very important!)”*
  - *“i have been searching to improve my trading algorithm”*
  - *“...getting it right (no back testing!)”*
  - *“Hindsight and insight is for children – real men operate on foresight :)”*
- Remember the **incentive to oversell timing ability**: This nonsense doesn’t have to convince *a lot of* people: just *enough* people.



## Spam email

Real-time trading on the derivative markets was a hobby until i struck Mandelbrot's cluster effect - 28 stop-losses in a row, wiping my portfolio many years ago. Since then i have been searching to improve my trading algorithm, and recently i have started to date SUE the bot - which has resulted in improving my financial trading algorithm getting it right (no back testing!), but predicting the next day's movement direction (very important!), and close-out magnitude (just get the freakin direction right!), with the results impressive to say the least. Forecast runs after the day's close-out for the next day prediction - making sure you experience that free flight feeling to take a position on a prediction without knowing where things are going next. Hindsight and insight is for children - real men operate on foresight :)

Actual	Forecast	Direction	Variance
0.86	0.83	Yes	3.86
2.83	2.56	Yes	9.59
1.99	1.87	Yes	6.10
-0.95	-0.83	Yes	12.37
2.71	2.49	Yes	8.24
-0.16	-0.11	Yes	32.91

# Factor timing: General comments

- **Bender et al. (2018):**
  - It is really important to ask: “What should the **relationship** between the **candidate signals** and **future factor returns** look like?”
  - “**Without strong investment rationale**, there is **too much danger** that **data mining** can drive the choice of signals.”

# Factor timing: “Practitioner” view

- **Asness (2016):**
  - “**Factor timing** is highly analogous to **timing the stock market**.”
  - “**Stock market timing** is **difficult** and should be done in very small doses, if at all.”
- **Arnott et al. (2016a):**
  - “Most investors **already practice** a form of **market timing** by **performance chasing**, which can **erode the benefits** of factor investing even when diversifying across factors having recent strong results.”
- **Asness et al. (2017):**
  - “We know that contrarian **market timing** is **very difficult**, and we find that **successful contrarian timing** of [factors] is **at least as difficult**.”
  - “From a multi-style perspective, it is **hard** for contrarian style timing to meaningfully **improve** upon simple strategic **diversification**.”
- **Lee (2017):**
  - “The author believes that attempting to **time factors** using other factors is **generally of limited value**...”
  - “Factor timers would be **better served** by focusing on the **underlying rationale** believed to **give rise to these premia**.”

# Factor timing: “Practitioner” view

- **Dichtl et al. (2019):**
  - “When ignoring transactions costs, the authors report significant excess returns to.. the factor timing... strategies, but consent that **active factor-forecasting** adds **little value after transaction costs** in their model specification.”
- **Van Gelderen et al. (2019):**
  - “We argue that **rather than timing factors** and factor managers, investors would be **better off** by using a **buy-and-hold strategy** and selecting a multifactor manager.”

# Factor timing: “Academic” view

- **Haddad et al. (2020):**

- “Market-neutral equity factors [**long-short** factors] are **strongly** and **robustly predictable**.”
- “Exploiting this predictability leads to **substantial improvement** in portfolio performance relative to static factor investing.”

- **Lioui and Tarelli (2020):**

- “We implement a dynamic allocation problem where the **investor attempts to time [long-short factor] portfolios**.”
- They basically take the long-short portfolios from FF, and then vary the **weights**:

SIZE factor	$SMB = \frac{1}{3} (Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3} (Big\ Value + Big\ Neutral + Big\ Growth)$
Value factor	$HML = \frac{1}{2} (Small\ Value + Big\ Value) - \frac{1}{2} (Small\ Growth + Big\ Growth)$

- “We employ two variables (**dividend yield** and **default spread**) to **predict** the conditional **expected abnormal returns** and market exposures of the assets”
- “**Significant out-of-sample Sharpe ratio improvements** and utility gains with respect to fixed-weights factor benchmarks.”

# Factor timing: “Academic” view

- **Laborda et al. (2016):**

- They predict the Fama and French Size (SMB) factor, with great success.

<b>SIZE</b> factor	$\text{SMB} = \frac{1}{3} (\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) - \frac{1}{3} (\text{Big Value} + \text{Big Neutral} + \text{Big Growth})$
-----------------------	--

- **Predictor variables** include: “interest rates”, “overall credit conditions”, “market risk aversion”, “economic sentiment”.
- “These variables and the inclusion of a risk-free asset in the investment opportunity set allow us to derive an optimal investment portfolio given by a **long position** on the **size factor** in periods of **economic expansion** and a **short position** in periods of **economic downturn** and financial turbulence that is compensated by a long position in the risk-free asset.”
- “Thus, we observe that an investor who follows optimized dynamic size factor strategies **attains a higher Sharpe ratio.**”

- Thoughts on the [academic] success of long-short factor timing:
  - Given what we know of long-short factors, transaction costs, investability etc...
  - **If you design a winning Monopoly strategy... does that make you a successful real estate investor?**

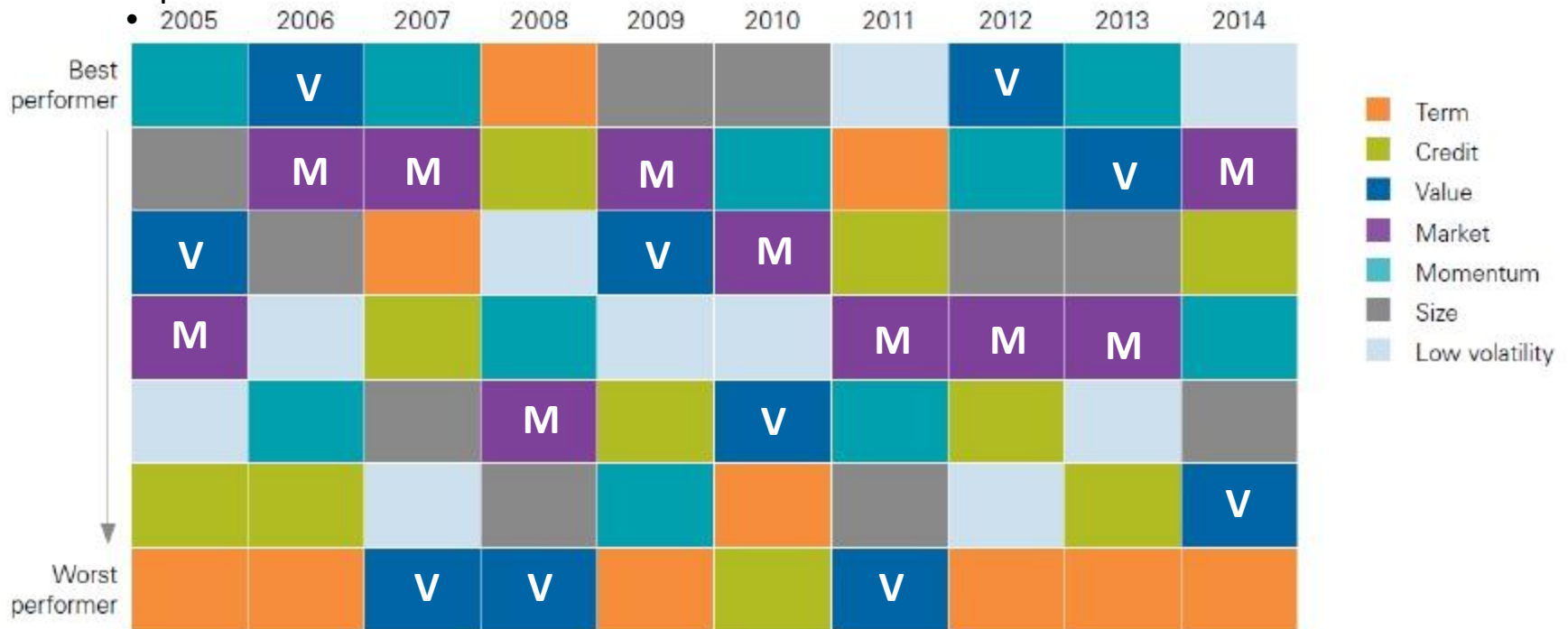
# Factor timing

- Some general questions, for which I've never seen nice answers.
- **Question 1: If factor timing “works”, compared to *what* does it “work”?**
  - Typically, factor timing “works” if investment results from [Model with factor timing predictions] outperforms the investment results from [benchmark].
  - Unfortunately, in the literature, [benchmark] is typically something uninspiring, like an [equally-weighted factor portfolio].
    - But [equally-weighted factor portfolio] tends to perform pretty badly.
  - Outperforming [benchmark] with terrible performance isn't *that* hard, as long as it isn't the market!
    - You can outperform an [equally-weighted factor portfolio] by dropping exposure to Size. You're welcome. 😊
- **Question 2: Why is timing *equity factors*, specifically, the source of so much excitement?**
  - If you're good at the “timing thing”, **why not time something better** – namely the aggregate stocks vs. bond allocations in your portfolio?



# Factor timing

- Question 1: If factor timing “works”, compared to *what* does it “work”?
  - Vanguard Research (2015): Ranking of annual returns of selected long-only factor portfolios



- Relative frequency of ranking:

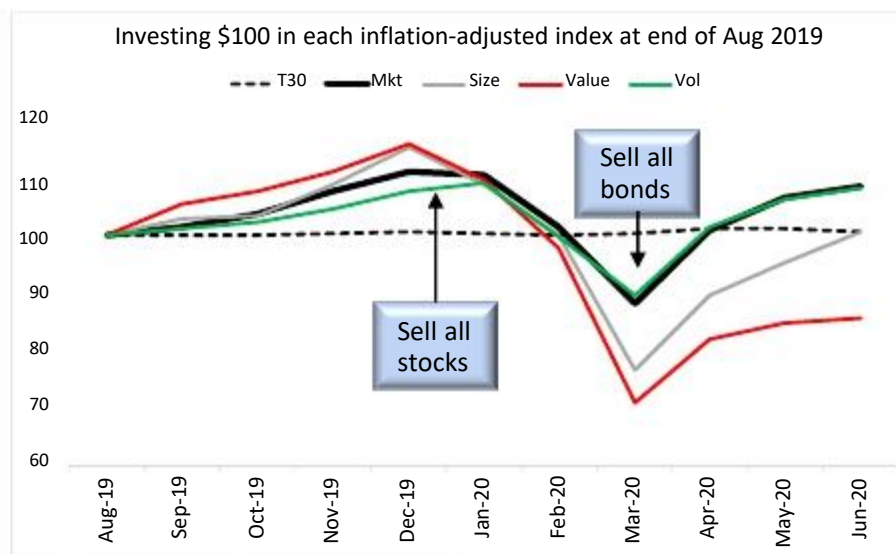
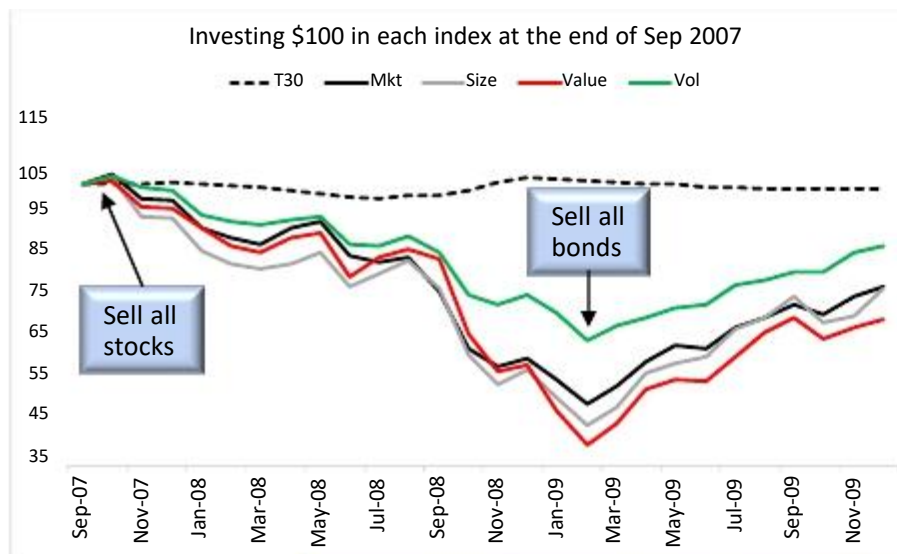
- M = Market.
- V = Value.

		Best								Worst
Freq /10	Market	40%	10%	40%	10%					
	Value	20%	10%	20%	10%	10%	30%			

- Factor timing has a very high bar to clear, namely passively holding market!!
- Getting **factor timing wrong** can result in really, really bad outcomes!!

# Factor timing: the wrong question?

- **Question 2: Why is timing *equity factors*, specifically, the source of so much excitement?**
  - If you're good at the "timing thing", **why not time something better** – namely the aggregate stocks vs. bond allocations in your portfolio?
- Example: GFC and Covid crash:
  - **Arnott et al. (2019):** "In periods of market stress, however, most diversification benefits can vanish as the **factors begin moving in unison...**"
  - If factors begin to move in unison.. what is the marginal benefit of "timing factors" when we most need it?



Why care about *which factor* is going to do well next, if you can **move out of stocks into bonds at the right time?**

# Overview of talk

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- ☐ How to profit reliably from factor investing.
- ☐ Reminder: Beating the market is hard.

# Factor performance: Past is (not) prologue

- **Malkiel (2014):**
  - “All [factor] portfolios have undergone **long periods of underperformance.**”
  - “There is considerable evidence of **reversion to the mean**, and periods of excess performance are often followed by periods of disappointing results.”
- **Arnott et al. (2016a):**
  - “We use a simple rule to show that **trend chasing destroys value.** Whatever is newly expensive is likely to have two attributes: **wonderful past returns and disappointing future returns.**”
- **Arnott et al. (2016b):**
  - “Many investors are **performance chasers** who in pushing prices higher create valuation levels that inflate past performance, reduce potential future performance, and **amplify the risk of mean reversion** to historical valuation norms”
- **Arnott et al. (2017a):**
  - “Using past performance to forecast future performance is **likely to disappoint.**”
  - “We find that a factor's **most recent five-year performance** is negatively correlated with its **subsequent five-year performance.**”
  - “By significantly extending the period of past performance used to forecast future performance, we **can improve predictive ability**, but the ~~forecasts are still negatively correlated~~ with **subsequent performance.**”
  - “The forecast is still essentially useless!”
- **Arnott et al. (2019):**
  - “We also believe that **shaping our forward expectations** by extrapolating ... past results... is **very dangerous.**”

# Factor performance: Word gets out...

- **McClean and Pontiff (2016):**

- Analyzes out-of-sample and **post-publication performance** of **97 factors**.
- **Returns** are **26% lower** out-of-sample.
- **Returns** are **58% lower** post-publication.
- “**Post-publication** declines are **greater** for **predictors** with **higher in-sample** returns.”
- “Our findings suggest that investors learn about mispricing from academic publications.”

- **Arnott et al. (2016b):**

- “Many of the most popular new factors and strategies have **succeeded solely** because they have **become more and more expensive**.”
- “Factor returns, net of changes in valuation levels, are much lower than recent performance suggests.”

- **Arnott, Kalesnik and Wu (2017):**

- “Yet, we must wonder, if **10,000 quants** are all **pursuing the same factor tilts**, how likely are they to add value?”

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# Profiting reliably from factor investing

- Case study #1: iShares/Blackrock
  - “iShares Core S&P U.S. Value ETF” [*IUSV*]:
    - Launch date: July 2000
    - Objective: “...seeks to track the investment results of an index composed of large- and mid-capitalization U.S. equities that exhibit value characteristics.”
    - Grossexpenseratio: 0.04%
    - YTD 2020 performance (1 Jan-26 Nov): - 3.06%
  - “iShares MSCI USA Value Factor ETF” [*VLUE*]:
    - Launch date: April 2013
    - Objective: “...seeks to track the performance of an index that measures the performance of U.S. large- and mid-capitalization stocks with value characteristics...”
    - Grossexpenseratio: 0.15%
    - YTD 2020 performance (1 Jan-26 Nov): - 4.41%
  - “iShares Focused Value Factor ETF” [*FOVL*]:
    - Launch date: April 2019
    - Objective: “...seeks to track the investment results of an index composed of U.S. large- and mid-capitalization stocks with prominent value characteristics.”
    - Grossexpenseratio: 0.25%
    - YTD 2020 performance (1 Jan-26 Nov): - 19.91%

# Profiting reliably from factor investing

- Case study #2: Vanguard
  - **“Vanguard Value ETF” [VTV]:**
    - **Launch date:** February 2004
    - **Objective:** “...seeks to track the performance of the CRSP US Large Cap Value Index, which measures the investment return of large-capitalization value stocks.”
    - **Gross expense ratio:** 0.04%
    - **YTD 2020 performance** (1 Jan-26 Nov): - 3.10%
  - **“Vanguard U.S. Value Factor ETF” [VFVA]:**
    - **Launch date:** March 2018
    - **Objective:** “... investing in stocks with relatively lower share prices relative to fundamental values as determined by the advisor.”
    - **Gross expense ratio:** 0.14%
    - **YTD 2020 performance** (1 Jan-26 Nov): - 3.10%
- YTD 2020 performance of the S&P 500 (1 Jan – 26 Nov): + 12.35%



# Profiting reliably from factor investing

- I'm not picking on ETF issuers here:
    - They're simply convenient to use as examples.
    - Information is publicly available.
  - **Bloomberg News (18 November 2020):** *"Renaissance, Two Sigma Drop as Quants Navigate Chaos"*
    - "Two of the hedge fund industry's quantitative powerhouses are getting tripped up this year as wild markets throw off their investing models."
    - "Two Sigma saw its **risk-premia strategy lose 11.5% this year** through last month [October 2020], according to documents seen by Bloomberg. "
    - "For quantitative funds that **specialize in so-called factor-investing**... November [2020] may have **added to the bruising**."
    - "Even for a firm such as AQR Capital Management, which was **tilted toward value stocks** in some of its portfolios, the pullback from momentum exposure was too big to overcome. The shift added to losses for the AQR Equity Market Neutral Fund, which was **down 19% this year** through Monday."
- At the risk of sounding cynical: I do think that monetizing the hype around factor investing (by charging high fees) is *the* way to profit most reliably, for the time being, from factor investing.

# I'm not dismissing factor investing

- **Arnott et al. (2019):**

- “It is no secret that factor returns have recently **fallen far short** of **investor expectations**.”
- “..we are **not dismissing factor investing**.”
- “We believe that the **factor literature** is **rich with insights**, many of which can be used to **deliver superior returns**.”

- For the record, my view on factor investing:
  - I also believe that “**factor literature** is **rich with insights**, many of which can be used to **deliver superior returns**.”

- How should you go about delivering superior returns?

# Bottom line: You're on your own

- **Bender et al. (2013):**
  - “Investors must **form their own belief** about what explains the historical premium and whether it is likely to persist.”
- **Melas (2016):**
  - “Investors making allocations to factors must **form their own beliefs** about what explains factor returns and whether they are likely to persist.”
- **Asness (2016):**
  - “Focus mostly on the **factors you believe in** over the very long haul, based on both evidence and economic theory.”

# Reminder: Beating the market is hard

- **Cochrane (1999):**

- “I emphasize a cautionary fact: **The average investor must hold the market.**”
- “You should only vary from a passive market index **if you are different from everyone else.**”
- “It **cannot be the case** that **every investor** should tilt his portfolio toward **value** or other high-yield strategies. If everybody did it, the phenomenon would disappear.”

- **Melas (2016):**

- “In reality, **market-cap benchmarks** are **extremely difficult** to **outperform** consistently.”

- **White and Haghani (2020):**

- “For factors with plausible risk-based explanations, the authors conclude that **even** in the presence of **significant factor premia**, the **market portfolio** is still likely to be **optimal for most investors.**”

- **Nes (2020):** Analyzing factor investing ETFs over Jan-2007 and Mar-2020.

- “This thesis does **not find** any statistically significant evidence of [factor] ETFs **outperforming ... broad, cap-weighted market indices.**”

Questions?