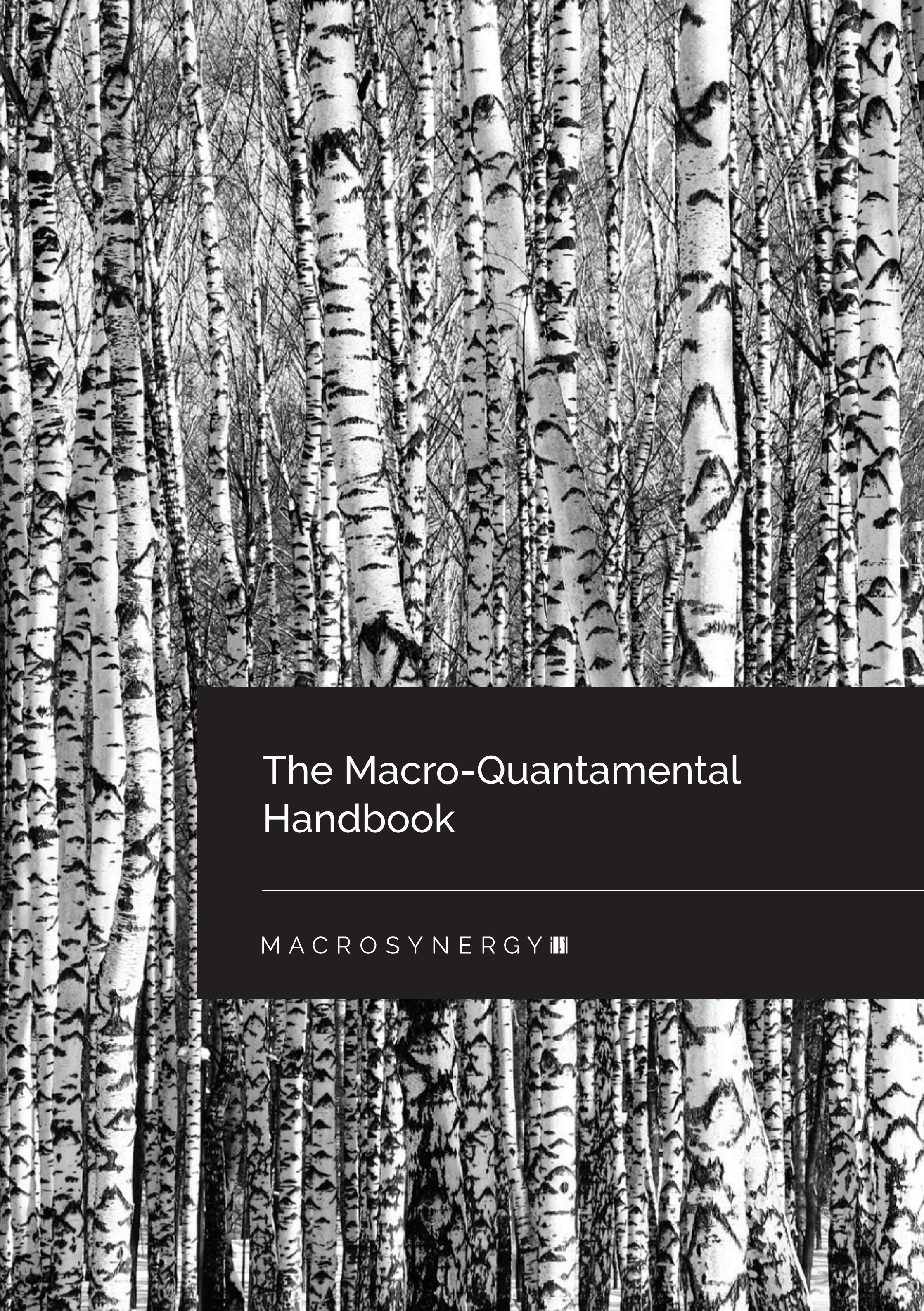


The Macro-Quantamental Handbook

MACROSYNERGY

About the author

For decades, macroeconomic data like gross domestic product, unemployment, or inflation rates have been utilized as valuable inputs to generate investment returns, largely by discretionary macro traders.

Macrosynergy's founding partners have been processing and analyzing macroeconomic data for over three decades. In 2005, they started to do so systematically by developing a data processing system, or macro-quantamental system, which helped them produce discretionary trading tools. In 2007, they began allocating capital to macro-quantamental systematic trading strategies utilizing the signals produced by the system and the tools.

Macrosynergy was established in 2009, and the company launched the Macrosynergy Trading Fund, a global macro investment fund, in January 2010.

In 2020, Macrosynergy transformed into a macro research and financial technology company and started its collaboration with J.P.Morgan to develop and scale the first global macro-quantamental system, the J.P.Morgan Macrosynergy Quantamental System ("JPMaQS"). JPMaQS is a service designed to facilitate the use of quantitative-fundamental ("quantamental") information in trading strategies, whether algorithmic or discretionary. It transforms macroeconomic concepts—such as growth, inflation, and balance sheets—into actionable indicators, enabling more informed trading decisions.

In partnership with J.P.Morgan, Macrosynergy provides data and content as a service to J.P. Morgan's institutional clients, offers investible indices using JPMaQS macro-quantamental indicators, and develops novel JPMaQS Macro Aware™ indices aimed to improve the risk/return profile of well-established benchmark indices.

Dr. Ralph Sueppel and Dr. Lasse Simonsen lead Macrosynergy's quantamental research and JPMaQS development effort. They, along with Macrosynergy's research team, are the primary contributors to *The Macro-Quantamental Handbook*.

Special thanks go to Elena Sueppel and Justine Recordon for coordinating the publishing of this handbook.

Disclaimer:
This Handbook has been prepared by Macrosynergy Limited ("Macrosynergy"), a company incorporated in the UK (Company number 06994336).

The material contained within the Handbook may not be reproduced in whole or in part under any circumstances without express written consent from Macrosynergy.

The information and opinions contained in this material are for education and research purposes. The information provided is not intended to provide a sufficient basis on which to make an investment decision.

Macrosynergy believes that the sources of this material are reliable. However, they make no representation or warranty, express or implied, regarding the accuracy or completeness of this material and accept no liability for any errors or omissions of any information, whether prepared by Macrosynergy or a third party.

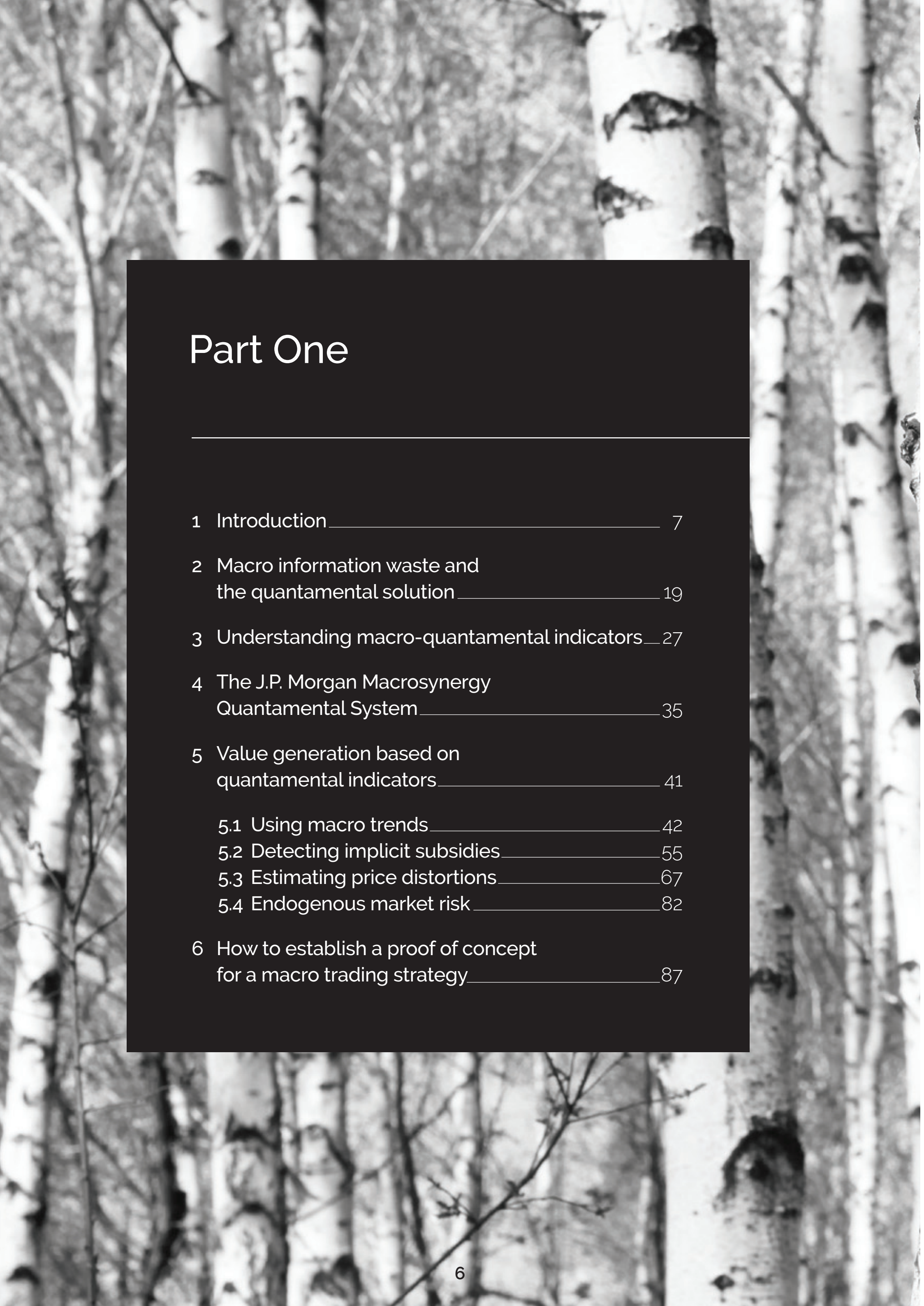
For further details of how we process personal data, please refer to our Privacy Policy on www.macrosynergy.com.

Published by Macrosynergy | www.macrosynergy.com

For JPMaQS online resources and contacts refer to Appendix 1 of this handbook.

First printing, April 2025.
Designed and produced by Hero Creative Ltd.

Contents



Part One

1 Introduction

Macro-quantamental indicators and trading signals are transformative technologies for asset management. They allow quants and portfolio managers to plug point-in-time fundamental economic information into systematic trading, backtesting, and statistical learning pipelines, removing an important barrier to information efficiency. While the predictive power of macro information for asset returns has been evident for decades, its use in systematic trading and research has remained rare. This disconnect reflects the historical difficulties of replicating past data and past analyses ("point-in-time" format), as well as the need for expert curation of data updates going forward.

Macro-quantamental signals make systematic trading more informed and anchor prices more firmly in economic reality. Value generation is not merely a zero-sum game but also a profit share from a more efficient financial system. The principles of quantamental success include the faster pricing of macroeconomic developments, correction of implausible risk premia, adjustment of evident price value gaps, and improved pricing of market "setback risks." Empirical evidence demonstrates macro-quantamental signals succeeding in many areas, including market timing, enhancement of trend-following, improvement of risk premium strategies, equity allocation, and higher-frequency information change-based strategies. Macro-quantamental signals also integrate neatly with statistical learning. This chapter is based on the blog How macro-quantamental trading signals will transform asset management[1].

What are macro-quantamental indicators and signals?

Generally, a quantamental indicator is a metric that combines quantitative and fundamental analysis to support investment decisions, such as equity valuation ratios or real interest rates. The metric must be a point-in-time information state, i.e., assign values to the date they became public knowledge, not when they occurred. More specifically, a macro-quantamental indicator is a time series of relevant macroeconomic information states designed for the development and backtesting of financial market trading strategies. Finally, a macro-quantamental trading signal is a time series of indications for market positions based on a model that incorporates quantamental indicators.

It is important not to confuse macro-quantamental indicators with standard macroeconomic indicators or standard macro trading signals:

- Macro-quantamental indicators are always public information states of the latest instance of economic development, such as GDP growth, earnings ratios, or real interest rates, as observed in real-time. This means that quantamental data are based on data vintages, i.e., time sequences of complete data histories. Vintages come about through extensions of data series, revisions, methodological changes, and re-estimates of underlying models. Quantamental indicators are principally designed to replicate what the market knew at any point in time in the past and to prevent any look-ahead bias in developing and evaluating trading strategies.
- Macro-quantamental signals are also quite different from standard systematic trading signals, which are mainly based on market prices and flows. Macro-quantamental signals directly inform on the activity, balance sheets, and sentiment of various parts of an economy. Some market data signals are also called "macro" but provide economic information only indirectly and are influenced by many other factors.

Why are macro-quantamental indicators new but not alternative data?

Macroeconomic information has been used extensively in discretionary trading for decades. However, point-in-time macro-quantamental information for systematic trading and backtesting has been rare because data generation has been tedious and expensive at the level of an asset manager. Standard economic databases are unsuitable because they overwrite data after revisions, omit publication and revision time stamps, and have, over time, modified conventions, adjustment factors, and underlying models. Backtests would be contaminated by hindsight.

A proper macro-quantamental indicator must, for any point in time in the past, display the value of an up-to-date economic report or analysis on that date. For example, the value of a short-term seasonally adjusted production trend on the 5th of October 2004 must be the percent growth rate for the latest available period based on the full-time series that was published on that date and adjusted by the seasonal factor that would have been used on that day. The dates at which the growth rates are timestamped are real-time dates. The periods to which the reported information refers are observation periods.

Observation period **Real-time date**	**Jan-90**	**Feb-90**	**...**	**Jun-23**	**Jul-23**	**Aug-23**	**Sep-23**	**...**	**Jun-24**	**Jul-24**	**Aug-24**	**Sep-24**	**Quantamental Indicator** **% oya (latest)**
...	...	...	...	...	...	...	...	...	...				
14/08/2024	100	100.4	...	402.9	404.7	402.7	404.1	...	410.1				**1.8**
15/08/2024	100	100.4	...	403.5	404.9	402.1	404.2	...	410.2	411.3			**1.6**
16/08/2024	100	100.5	...	403.5	404.9	402.1	404.2	...	410.2	411.3			**1.6**
...	...	...	...	...	...	...	...	...	...				...
30/08/2024	100	100.5	...	403.5	404.9	402.1	404.2	...	410.2	411.3			**1.6**
02/09/2024	100	100.4	...	403.1	404.2	402.8	404.1	...	409.2	408.9			**1.2**
03/09/2024	100	100.4	...	403.1	404.2	402.8	404.1	...	409.2	408.9			**1.2**
...	...	...	...	...	...	...	...	...	...				...
13/09/2024	100	100.4	...	403.1	404.2	402.8	404.1	...	409.2	408.9			**1.2**
16/09/2024	100	100.3	...	403.3	403.2	403.2	403.9	...	409.6	408.2	409.7		**1.6**
17/09/2024	100	100.3	...	403.3	403.2	403.2	403.9	...	409.6	408.2	409.7		**1.6**
...	...	...	...	...	...	...	...	...	...	...	...		...
30/09/2024	100	100.3	...	403.3	403.2	403.2	403.9	...	409.6	408.2	409.7		**1.6**
01/10/2024	100	100.3	...	403.4	402.4	402.4	404.1	...	409.4	409.1	410.5		**2.0**
02/10/2024	100	100.3	...	403.4	402.4	402.4	404.1	...	409.4	409.1	410.5		**2.0**
...	...	...	...	...	...	...	...	...	...	...	...		...
14/10/2024	100	100.3	...	403.4	402.4	402.4	404.1	...	409.4	409.1	410.5		**2.0**
15/10/2024	100	100.4	...	402.9	402.2	402.2	404.2	...	409.3	408.3	410.6	414.5	**2.5**
16/10/2024	100	100.4	...	402.9	402.2	402.2	404.2	...	409.3	408.3	410.6	414.5	**2.5**

Table 1.1: Vintage matrix for a quantamental indicator with one underlying series

This real-time data principle implies that even the simplest quantamental indicator is principally based on a two-dimensional data set (view Table1.1).

- The first dimension is the timeline of real-time dates. It marks the progression of the market's information state. A change in values on this timeline marks updates of public information.
- The second dimension is the timeline of observation dates. Each real-time date records the full history of an economic indicator, which is the basis for calculating the quantamental indicator, i.e., a vintage. A change in values along this timeline marks a change in an economic state according to the knowledge of the real-time date.

Hence, the underlying data set of a simple quantamental indicator (that uses only one economic time series) is a sequence of vintages. It is like an expanding data frame with a row index of progressing real-time dates and a column index of expanding observation periods. If the quantamental indicator requires more than one economic time series for calculation, such as the external trade balance-to-GDP ratio, the underlying data structure becomes 3-dimensional, with the third dimension being the index of indicators.

A quantamental database requires a large vintage data warehouse, which is hundreds of times the size of a comparable regular economic database. That warehouse must ingest information from a wide range of statistical agencies, research institutes, and data aggregators. Official vintage archives are often poorly maintained for lack of widespread interest and require quality control and "repairs". Moreover, not all vintage information is available in archives. The progression of model-driven quantamental indicators such as nowcasts must be estimated through a sequential evolution of models and their parameters.

Due to these challenges, it was not until 2023 that the first industry-wide source of macro-quantamental information for institutional investors was introduced: the J.P. Morgan Macrosynergy Quantamental System (JPMaQS) (please view Chapter 4: The J.P. Morgan Macrosynergy Quantamental System for more details[2]). It is the first service that allows the systematic evaluation and trading of macro-quantamental indicators, making macro-quantamental trading strategies feasible and affordable for the entire asset management community.

Why are macro-quantamental indicators a "game changer"?

The general availability of macro-quantamental indicators means that macroeconomic information can be used in systems similar to price data, whether it is for purely algorithmic strategies or for systematically supported discretionary trading. This broadens the scope of evidently relevant features that can be used in systematic trading, giving it a new and potentially critical edge over traditional discretionary trading. While systematic signals are generally simple compared to the reasoning of discretionary managers, they can incorporate much more information than a human; and the field of macroeconomic information is vast. At a global scale, not even specialized economists can keep up with relevant developments in all countries with sizable financial markets. Only quantamental signals can do that.

At present, systematic trading is dominated by price and financial flow data, which are easier to understand and backtest. However, macroeconomic information seems similar in importance to prices and flows.

- Academic theory has long established that all financial contract prices are part of a broader macroeconomic equilibrium. For example, bond prices reflect the demand and supply of credit and balance savings and investment at the macroeconomic level. Similarly, exchange rates balance the demand for goods and assets across currency areas. This means that if macroeconomic conditions outside the financial markets change relative to expectations or perceptions, so must prices in the financial market.
- Financial markets cannot possibly be fully macro information efficient. Information goes to waste due to research costs, trading restrictions, and external effects. Please view Chapter 2: Macro information waste and the quantamental solution for more details[3]. The cost-benefit trade-off manifests in the form of rational inattention. The theory of rational inattention argues that market participants cannot continuously process and act upon all information, but they can set priorities and choose the mistakes they are willing to accept (view post Rational inattention and trading strategies[4]). Moreover, research alone does not produce efficient markets. Financial markets research translates into price information only if and when it is acted upon.

The evident relevance and rational neglect of macroeconomic information explain why specialized discretionary macro trading has been so profitable over the past decades. This also suggests that macro-quantamental signals will make systematic trading more informed and more "grounded" in the economic developments outside financial markets. Hence, value generation is not merely a zero-sum game, where the better-informed trader outsmarts the less informed market participants, but rather manifests in the form of a profit share from more efficient financial systems and economies. Macro-quantamental strategies contribute to a core social function of the asset management industry, i.e., the provision of informative prices for the efficient allocation of scarce economic resources.

How do macro-quantamental indicators create investment value?

Value generation through point-in-time macro information is no great mystery and can broadly be classified into four principles. Please view Chapter 5: Value generation based on quantamental indicators for more details[5]:

5.1 Using macro trends	5.2 Detecting implicit subsidies
5.3 Estimating price distortions	5.4 Endogenous market risk

Following macroeconomic trends:

Macroeconomic trends predict asset returns for two principal reasons:

- they affect investors' attitudes toward risk, and
- they influence the expected risk-neutral payoff of a financial contract.

For example, an increase in inflation typically raises fear for monetary stability and increases expected future interest rates simultaneously. With rational inattention, point-in-time information on economic trends, which can encompass a wide range of indicators and countries, is never fully priced. The relevance and predictive power of point-in-time macro trends have been demonstrated in applied research for all major asset classes: fixed income, foreign exchange, equities, commodities, credit derivatives, and cross-asset return correlation (please view Section 5.1: Using macro trends in this handbook for more details[6]).

Detecting implicit subsidies:

Implicit subsidies in financial markets are premia paid through transactions where there are motives other than conventional risk-return optimization. They manifest as expected returns over and above the risk-free rate and conventional risk premia (please view Section 5.2: Detecting implicit subsidies in this handbook for more details[7]). Non-profit transaction motives include monetary policy, public interventions to safeguard financial stability, convenience yields of certain assets that accrue to banks and corporates, non-standard risk aversion, and behavioral biases, such as salience bias and loss aversion. Implicit subsidies are a bit like fees for services, except that they are opaque rather than openly declared. Macro-quantamental indicators can help detect implicit subsidies by tracking plausible motives, such as deflation risk, or tracking valuations and expected returns, such as risk-adjusted real carry on currencies. Detecting implicit subsidies is information-intensive but often creates stable risk-adjusted value.

Detecting price distortions:

Price distortions are conspicuous price-value gaps. They arise from inefficient flows and prevail as long as a sizable share of market participants is either unwilling or unable to respond to obvious dislocations (please view Section 5.3: Estimating price distortions in this handbook for more details[8]). There are many causes of inefficiencies, including risk management rules, liquidity disruptions, mechanical rebalancing rules and government interventions. Macro-quantamental indicators help identify distortions through fundamental valuation metrics and measures of market disruptions. For example, terms-of-trade and purchasing power parity estimates assist in tracking currency overvaluation, while bank lending surveys and central bank liquidity measures can indicate financial market stress.

Tracking endogenous market risk:
Endogenous risk refers to uncertainty resulting from financial market positioning, as opposed to uncertainty about traded assets' fundamental value. Endogenous market risk often manifests as feedback loops after some exogenous shock hits the market. An important type is setback risk, which refers to the asymmetry of the upside and downside potential of a trade that arises from market positioning (please view Section 5.4: Endogenous market risk in this handbook for more details[9]). Setback risk is a proclivity to incur outsized mark-to-market losses even if the fundamental value proposition of the trade remains perfectly valid. This makes it the natural counterweight to popular positioning. A useful two-factor model for detecting setback risk can be based on market positioning and exit risk. The highest setback risk is characterized by crowded positions that face an incoming shock that most investment managers have not considered. Macro-quantamental indicators help track economy-wide positioning risk, for example, by monitoring capital flows, current account deficits, and governing borrowing requirements.

Proofs of concept

There is increasing evidence of the relevance of macro-quantamental trading signals across asset classes, trading frequencies, and signal-generation principals. This section summarizes this evidence to the extent that it has been documented in the Quantamental Academy[10]:

Market direction and timing

Simple macro-quantamental signals have displayed significant predictive power of directional returns across and between asset classes. Importantly, those signals need not be optimized; they merely follow standard economic theory and common sense.

For example, a single balanced "cyclical strength score" based on point-in-time quantamental indicators of excess GDP growth, labor market tightening, and excess inflation has displayed significant predictive power for equity, FX, and fixed income returns, as well as relative asset class positions. The direction of relationships has always been in accordance with the theoretical priors of macroeconomics (view post Macroeconomic cycles and asset class returns[11]). Similarly, relative central bank intervention liquidity trends, which inform on the market support of monetary policy, have been predictors of the future relative performance of assets across different currency areas (view post Intervention liquidity[12]). Finally, bank lending surveys help predict the relative performance of equity versus duration positions, with signs of stronger credit favoring business growth and expanding leverage. Conversely, signs of tightening credit supply bode for a weaker economy and more accommodative monetary policy, benefiting duration versus equity positions (view post Equity versus fixed income: the predictive power of bank surveys[13]).

Enhancements of standard trend following
Classic trend following is based on market prices. Market trends generate value in the presence of behavioral biases and rational herding. By contrast, macro trends track relevant states of the economy based on fundamental data. Notably, macro and market trends have complementary strengths. While market trends are timelier, macro trends are more specific in information content (view post Trend following: combining market and macro information[14]). Jointly they can produce more value than individually.

Indeed, market price trends often foster economic trends that eventually oppose them. Theory and empirical evidence support this phenomenon for equity markets and suggest that macro headwind (or tailwind) indicators are powerful modifiers of trend-following strategies. For example, if one modifies standard price trend signals of equity index futures in developed markets by macro-quantamental indicators of labor markets and inflation, the resulting modified signal displays greater predictive power and material increases risk-adjusted returns (view post Equity trend following and macro headwinds[15]).

A similar effect can be found in foreign exchange. A currency's positive FX forward return trend is less likely to be sustained if concurrent economic data signal a deterioration in the local economy's competitiveness. Empirical evidence shows that standard global FX trend following would have benefited significantly merely from adjusting for changes in external balances (view post FX trend following and macro headwinds[16]).

Enhancement of carry strategies
Carry can be defined as a return for unchanged market prices and is easy to calculate in real-time across assets. It is a legitimate basis for tracking risk premia and implicit subsidies. However, conceptually, carry signals can be improved upon through integration with macro-quantamental concepts.

For example, an FX forward-implied carry signal value can typically be enhanced by considering inflation differentials and cross-country differences in economic performance (view Modified and balanced FX carry[17]). Also, carry metrics can be enhanced by currency over or undervaluation, using purchasing power parity-based valuation estimates that are partly or fully adjusted for historical gaps (see Advanced FX carry strategies with valuation adjustment[18]).

There are two simple ways to enhance carry strategies with economic information:

- The first increases or reduces the carry signal depending on whether relevant economic indicators reinforce or contradict its direction. The output can be called **"modified carry"**. It is a gentle adjustment that leaves the basic characteristics of the original carry strategy intact.
- The second method equalizes the influence of carry and economic indicators, thus diversifying over signals with complementary strengths. The combined signal can be called **"balanced carry"**. Empirical analysis suggests that both adjustments would have improved the performance of FX carry strategies (view Modified and balanced FX carry[19]).

Commodity carry signals have also profited from quantamental enhancements. Carry on commodity futures contains information on implicit subsidies, such as convenience yields and hedging premia. Its precision as a trading signal improves when incorporating adjustments for inflation, seasonal effects, and volatility. There is strong evidence for the predictive power of various metrics of real carry with respect to subsequent future returns and stylized naïve PnLs based on real carry points to material economic value (view Commodity carry as a trading signal – part 2[20]).

Equity allocation

Macroeconomic trends affect stocks differently, depending on their lines of business and their home markets. Hence, point-in-time macro indicators can support two types of investment decisions:

Allocation across SECTORS within the same COUNTRY

Allocation across COUNTRIES within the same SECTOR

A number of plausible quantamental categories have proven relevant for predicting relative sectoral and relative country returns (view Macro trends and equity allocation: a brief introduction[21]).

– There is sound reason and evidence for the predictive power of macro indicators for relative sectoral equity returns. However, the relations between economic information and equity sector performance can be complex. Considering the broad range of available point-in-time macro-categories that are now available, statistical learning has become a compelling method for discovering macro predictors and supporting prudent and realistic backtests. For developed equity markets, a simple learning process produces signals that are positive predictors for the relative returns of all Global Industry Classification Standards (GICS) sectors versus a broad basket. Combined into a single strategy, these signals create material and uncorrelated investor value through sectoral allocation alone (view Macro factors and sectoral equity allocation[22]).
– Success in cross-country macro trading often relies on differentiating indicators related to monetary policy and corporate earnings growth in local currency. A straightforward, non-optimized composite score of quantamental indicators across countries could have added significant value to an equity index futures portfolio beyond simple risk-parity exposure. Furthermore, a purely relative value equity index futures strategy across countries would have produced respectable long-term returns (view Cross-country equity futures strategies[23]).

Higher-frequency macro signals

Information on economic states often changes gradually. However that does not mean that macro-quantamental signals are necessarily low frequency. The first differences of a macro-quantamental time series are proxies of market information state changes, i.e., point-in-time updates of recorded economic developments. They can refer to a specific indicator or a broad development, such as growth or inflation. The broader the economic concept, the higher the frequency of changes. Information state changes are valuable trading indicators. They provide daily or weekly signals and naturally thrive in periods of underestimated escalatory economic change, adding a layer of tail risk protection.

For example, one can produce signals-based information state changes to interest rate swap trading across developed and emerging markets, focusing on growth, sentiment, labor markets, inflation, and financing conditions. Normalized information state changes are comparable across economic groups and countries and, hence, can be aggregated to local and global signals. The predictive power of aggregate information state changes has historically been strong, with material and consistent PnL generation (view Macro information changes as systematic trading signals[24]).

Integration with statistical learning

For almost all types of financial contracts and positions, one can build a wide range of candidate macro-quantamental signals based on theory and plausibility. However, a frequent challenge is to select from these candidates and combine them with a method that is consistent across time and allows realistic backtesting. This is where statistical learning and macro-quantamental signals are complementary.

Statistical learning offers methods for sequential model selection, as well as associated hyperparameters, for signal generation, thus supporting realistic backtests and automated operation of strategies. It can be applied to sequential optimization of three important tasks: feature selection, return prediction, and market regime classification (view Optimizing macro trading signals – A practical introduction[25]).

For example, regression-based statistical learning is a simple and easy-to-understand method for combining macro indicators into a single trading signal (view Regression-based macro trading signals[26]). It has proven its value for combining a range of macro factors into a single FX trading signal (view FX trading signals with regression-based learning[27]). Notably, signals based on regression coefficients can be adjusted for statistical precision to align intertemporal risk-taking with the predictive power of signals (view How to adjust regression-based trading signals for reliability[28]).

CONTENTS

Resistance to the macro-quantamental expansion

The industry-wide availability of quantamental indicators has principally connected the worlds of macroeconomics and systematic trading. This is irreversible. However, penetration of this new technology affects the investment process at its core and, hence, clashes with institutional inertia and individual resistance:

Congested data pipelines:

Information technology has allowed the production of a growing range of data sets, often called “alternative”. The investment management industry is a natural target of their monetization. However, asset managers face margin and cost pressures and need to filter the flood of quantitative information. They require time for exploration and adaptation. Macro-quantamental indicators may be new formats rather than new types of information. Still, they are classified as “new datasets” and, hence, often travel on a crowded procurement and exploration road.

Distrust towards macroeconomics:

Producing investment value with macro-quantamental indicators works best with basic domain knowledge of macroeconomic statistics and economic theory. This is not popular with many systematic strategy developers who mostly hail from the realms of software engineering, data science, and mathematical finance. The distrust of macroeconomics is enhanced by the impenetrable jargon of economic research papers and the notorious tendency of economists to emphasize disagreements rather than consensus.

Exclusivity:

A quantamental system is what economists would call a **“club good”**, i.e., a type of service that benefits from having multiple but controlled numbers of users, a bit like a tennis or swimming club. For example, JPMaQS, the first global quantamental system, is mainly for participating institutional investors. T-6 month data is free for research; a subscription fee is required for a complete service.

Misunderstandings of costs:

A macro-quantamental “club” may charge higher fees than a standard economic database. However, tradable and non-tradable data are not comparable services, as the former includes modelling and refinement that otherwise would accrue as costs with the data user. Moreover, the cost of quantamental indicators relative to related trading profits is typically marginal. Indeed, for research purposes, up to the proof of concept of a quantamental signal, quantamental indicators are typically free. Compared to ad-hoc in-house development of quantamental indicators, access to a quantamental system usually implies significant cuts in development times and costs.

Figure 1.1: Resistance to the macro-quantamental expansion

2 Macro information waste and the quantamental solution

Financial markets are not macro information efficient. This means that investment decisions miss out on ample relevant macroeconomic data and facts, resulting in missed opportunities to improve returns. Information goes to waste due to research costs, trading restrictions, and external effects. Evidence of macro information inefficiency includes sluggishness of position changes, the popularity of simple investment rules, and the prevalence of herding. A simple and practical enhancement of macro information efficiency is the construction of quantamental indicators.

A quantamental indicator is a time series that represents the state of an investment-relevant fundamental feature in real-time. The term ‘fundamental’ means that these data inform directly on economic activity, unlike market prices, which inform only indirectly. The key benefits of quantamental indicators are that [1] they fit machine learning pipelines and algorithmic trading tools, thus making a broad set of macro information tradable; [2] they support the consistent use of macro information; and [3] they can be applied across traders (or programs), strategy types, and asset classes and are, thus, cost-efficient. This chapter is based on the blog Macro information waste and the quantamental solution[1].

What is macro information efficiency?

Macro information here refers to public information on the economy and its key sectors that are relevant for the pricing of assets and derivatives. This type of information includes economic data (on growth, inflation, confidence, and so forth), government and corporate balance sheets, financial market data (including turnover and open interest), social and political developments, and even environmental and weather trends.

The information efficiency of an asset market is defined as the extent to which the price of the asset reflects available information. Importantly, the efficiency of a market does not mean efficient use of information across all market participants. Different individuals or institutions have different capacities to buy, collect and use data. This is one key reason why there is trading and rational herding behavior (view Rational informational herding[2]). Herding is rational for uninformed but flexible traders when important releases are forthcoming and some market participants are likely to have private advance information. An information-efficient market produces, researches, and applies macro information to the extent that investment returns and social benefits exceed information costs.

Why are markets not (macro) information efficient?

The principal obstacles to information efficiency are costs, trading restrictions, and external effects.

> "...because information is costly, prices cannot perfectly reflect the information which is available, since if it did, those who spent resources to obtain it would receive no compensation."
> —Grossman and Stiglitz

In their seminal article "On the Impossibility of Informationally Efficient Markets" Grossman and Stiglitz explained:

> "...since price-relevant information comes at a cost it will only be procured to the extent that inefficient markets allow translating it into sufficient returns... The only way informed traders can earn a return on their activity of information gathering, is if they can use their information to take positions in the market which are 'better' than the positions of uninformed traders... Hence the assumptions that all markets, including that for information, are always in equilibrium and always perfectly arbitraged are inconsistent when arbitrage is costly."
> —Grossman and Stiglitz

This theory shows what practitioners already know. Investment in information involves a trade-off between cost and return with no guarantee that markets set asset prices close to their fundamental value.

Theory and practice show that investment managers only collect information and engage in research if costs are contained, the overall market is uninformed, and their own information advantage does not become general knowledge:

- First, information cost must not exceed related expected returns. Genuine value-generating macroeconomic and financial research requires experience, quantitative skills and systems, and a lot of legwork. This means that information costs easily add up to large numbers in practice. Many essential areas of this research, such as real-time economic data or advanced modeling, are beyond the scope of most portfolio management teams, even at large institutions. Thus, standard economic data are notoriously hard to interpret and require considerable adjustments. Economists often disagree on their interpretation of data and do not normally update their predictions instantaneously. Even the most popular and highest-quality economic data, such as U.S. labor market reports, need in-depth research to extract information (view Efficient use of U.S. jobless claims reports[3]). Moreover, forecasts are not easily comparable across countries due to different conventions and biases. All this gives rise to **rational information inattentiveness** of markets (view Information inattentiveness of financial markets[4]). This means that market participants update their information set sporadically, rather than continuously. Rational inattentiveness reflects costs of acquiring information or costs of re-optimizing investment decisions. There is empirical evidence that inattentiveness causes sticky expectations and goes some way in explaining price momentum after important relevant news, such as corporate earnings releases (view Sticky expectations and predictable equity returns[5]). Moreover, understanding the relationship between economic information and asset prices requires experience and econometric skills. Data science has come a long way in providing powerful tools for analysis and model construction. However, in the data-constrained macro space, the success of statistical models hinges on good judgment and a real in-depth understanding of methods, models, and data, all of which remain in short supply. Therefore, most institutional investors prefer simple relations, often in the form of three main categories of risk premia strategies, i.e. carry, momentum, and relative value (view Risk premia strategies[6]).
- Second, investor research only pays off when the overall market is not already well-informed. Put simply, research must result in a significant information advantage. This can be a serious obstacle because the information content of prices with respect to known fundamentals tends to grow faster than the information content of private research. This discourages fundamental research and can lead to over-reliance on price information (view The dominance of price over value[7]). Experimental research has confirmed that traders do not invest in information if they believe that others have already done so and that market prices already reflect this research (view Information inefficiency in market experiments[8]). For a profitable investment management business, it is crucial to invest in relevant information where or when others do not.
- Third, the information advantage must remain confidential. In particular, market makers must not suspect that their counterpart is in possession of superior information (view A theory of information inefficiency of markets[9]). A value trader with a reputation of being well informed is easily 'front run' when giving orders to market makers.

> "If I know that you are rational, and I know that you have different information than I have, when I see you trade and the price rises I can infer the importance of your information and thus I should change my own valuation."
> —Bouchaud, Farmer and Lillo (2009)

It is also evident that research alone does not produce efficient markets. Analytical work translates into price information only if it is acted upon. Alas, the link between research and actual investment flows is often tenuous, for various reasons:

Rules and regulations

Taking positions in accordance with research is frequently obstructed by institutional rules and regulations. For example, banks and brokers are often not allowed to trade on their analysts' views before those have been published. Meanwhile, many funds face limitations to leverage and short selling or are prohibited from investing in specific asset classes, currencies and sectors.

Market access / trading costs

For some institutions market access is limited and trading costs can be prohibitively high. For example, in OTC (over-the-counter) markets bid-offer spreads vary across counterparties (view Understanding bid-offer spreads in OTC markets[10]) favoring clients with high volumes and sophistication. Since institutional investment strategies in forwards, swaps, and options that are sensitive to transaction cost implementation depend on the institution's standing with market makers.

Trust between PMs and research

Often investment managers simply do not fully trust their researchers, possibly due to conflicts of interest. Portfolio managers sometimes denigrate research to elevate their own role in profit generation. Researchers sometimes gear their research towards company politics and reputation rather than investment value.

Behavioral biases

There is evidence that financial decision-making under uncertainty is far from rational and subject to a range of behavioral biases, such as the illusion of control, anchoring bias, sunk-cost bias, and gambler's fallacy (view The irrational neglect of optimal betting strategies[11]).This implies irrational neglect of optimal strategies.

What is the evidence for macro inefficiency?

Macro information inefficiency is consistent with evidence of numerous behavioral biases of both retail and professional investors.

Evidence of numerous behavioral biases of both retail and professional investors

Survey evidence suggests that retail investors adjust positions sluggishly to changing beliefs and that their beliefs themselves defy classic rationality (view Retail investor beliefs[12]). Sluggishness manifests in two ways. First, the sensitivity of portfolio choices to beliefs is small. Second, the timing of trades does not depend much on belief changes. Contrary to standard rationality, investors cling stubbornly to diverse beliefs with little convergence overtime.

Macro information inefficiency also explains the dominance of simple investment rules with little fundamental research. In practice, asset allocation often just follows past performance (view How U.S. mutual funds reallocate assets[13]), simplistic highly stylized factors (view Basic factor investment for bonds[14]), risk parity and valuation ratios (view Concerns over risk parity trading strategies[15]), or simply market capitalization and benchmark index conventions (view The passive investment boom and its consequences[16]). Even active portfolio managers often find it more practical to produce "fake alpha" through receiving risk premia on exposure to non-directional conventional factors and strategies rather than to generate true investor value (view Fake alpha[17]).

Furthermore, information inefficiency explains why momentum trading has been a profitable trading strategy, even in the best researched and most liquid markets (view Trend following in U.S. equities[18]) and is widely used as a trading style to protect against adverse macro trends (view Basic theory of momentum strategies[19]).There is ample evidence of herding and sequential dissemination of information in markets with great macroeconomic importance, including currencies (view Herding in financial markets[20] and A theory of herding and instability in bond markets[21]). And there is evidence that trend following based on simple fundamentals has yielded significant returns in equity markets in past decades (view Fundamental trend following[22]). All these phenomena testify to the sluggishness of market responses to broad shifts in fundamental conditions.

Finally, experimental research has added evidence for mispricing of assets relative to their fundamental values. Academic studies support a wide range of causes for such mispricing, including asset supply, peer performance pressure, overconfidence in private information (view Overconfidence and inattention as asset return factors[23]), speculative overpricing, risk aversion, confusion about macroeconomic signals and – more generally – inexperience and cognitive limitations of market participants (view Why financial markets misprice fundamental value[24]).

Figure 2.1: Evidence of numerous behavioral biases of both retail and professional investors

"Laboratory experiments... find that market efficiency is reduced when the fundamental value of stocks is volatile... The more volatile the fundamental value, the more the informational efficiency is reduced when the fundamental value of stocks is volatile... Also, participants under-react to information announcements. This under-reaction, which is more pronounced in markets with information asymmetry between subjects... is not corrected during trading periods." —Bouattour and Martinez (2019)

Enhancing macro efficiency with quantamental indicators

Investment managers can contribute to and benefit from information efficiency. A simple and practical approach is [1] to create indicators with meaningful macroeconomic and market information and [2] to condense them into meaningful conceptual **quantamental indicators and related trading factors** that can guide investment strategies.

Fundamental features derive from the macroeconomic, social (macro behavioral), corporate and environmental space. Real-time dating means that indicator values correspond to the state of public information at the associated date. Values change in accordance with new data releases or re-estimations of relevant models. The impact of new data releases should be calculated based on data vintages, i.e. the state of time series at a specific release date. Re-estimation can be simulated through statistical learning.

The usage of quantamental indicators and factors has great benefits, particularly in the macro space:

- Quantamental factors fit machine learning pipelines and algorithmic trading tools, thus making a broad set of macro information tradable. In international macro trading, there are far too many economic data series to keep track of, even for the most diligent investment manager. Selected pre-filtered macro factors effectively outsource part of the production of information to research and data science. Importantly, one factor can be used by multiple traders or programs, as each will customize its own version and implementation around it. Thereby, fixed costs in the production of factors and – more importantly – their building blocks can be shared across traders, making investment research more cost-efficient.
- Quantamental factors support consistency in the application of fundamental information. Oftentimes investors are myopic: they overrate "fashionable" factors that happened to coincide with recent market moves, regardless of causality and long-term relations. This constitutes an informal version of "overfitting" of information (view What markets can learn from statistical learning[25]), also called **"scapegoat theory"** (view The misinterpretation of exchange rate fundamentals[26]). Overfitting leads to misinterpretation of fundamental information, crowded positions and setback risk.
- Quantamental macro factors are applicable across markets and asset classes. This means that they are highly relevant for multiple strategies and are more cost-efficient than sporadic bespoke research. Detecting changes in economic growth, for example, matters for both equity and FX strategies. If returns across asset class strategies have little or no correlation (view Hints for cross-country equity strategies[27]), quantamental factors can become important building blocks for diversified multi-strategy portfolios.

For practical purposes and to avoid double-counting, misinterpreting and forgetting information, it is helpful to structure quantamental factors into three groups:

Valuation gaps

Valuation gaps are differences between the market price of an asset or derivative and its estimated value. There are two ways to track them: [1] directly estimating fundamental value, often using discounted cash flows, and comparing it to the market price—this approach requires complex modeling and patience for payoffs; [2] indirectly tracking or "nowcasting" the trend in key valuation-relevant factors, and estimating gaps between actual values and market perceptions. Macroeconomic trends are powerful asset return factors because they affect both risk aversion and risk-neutral valuations (view Section 5.1: Macro trends[28]).

Implicit subsidies

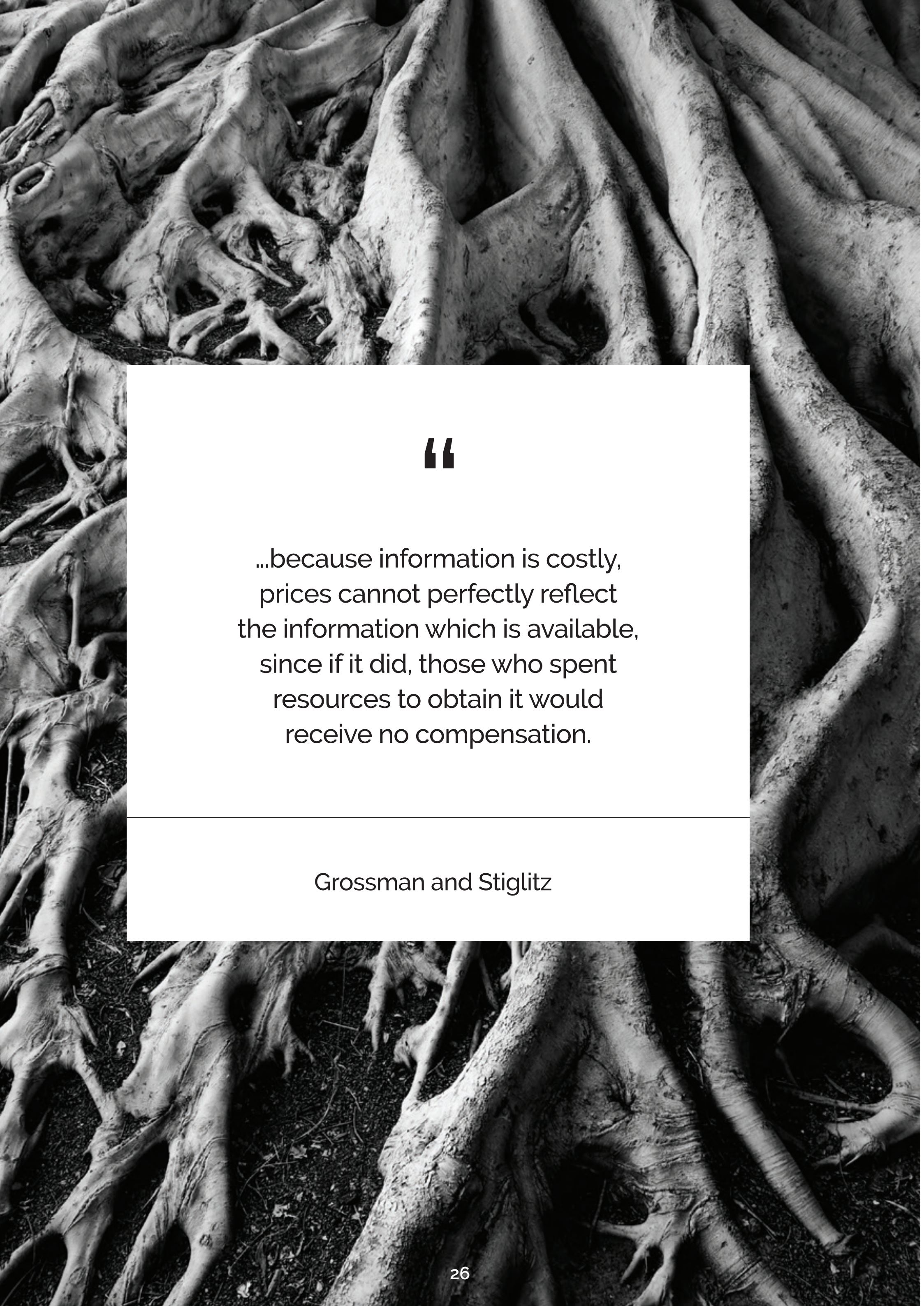
Implicit subsidies in financial markets are premia paid through transactions that have motives other than conventional risk-return optimization. They manifest as expected returns over and above the risk-free rate and conventional risk premia. Implicit subsidies are a bit like fees for services. Typically, subsidies are paid by central banks, governments, highly-regulated institutions or non-financial institutions (view Section 5.2: Implicit subsidies[29]).

Endogenous market risk

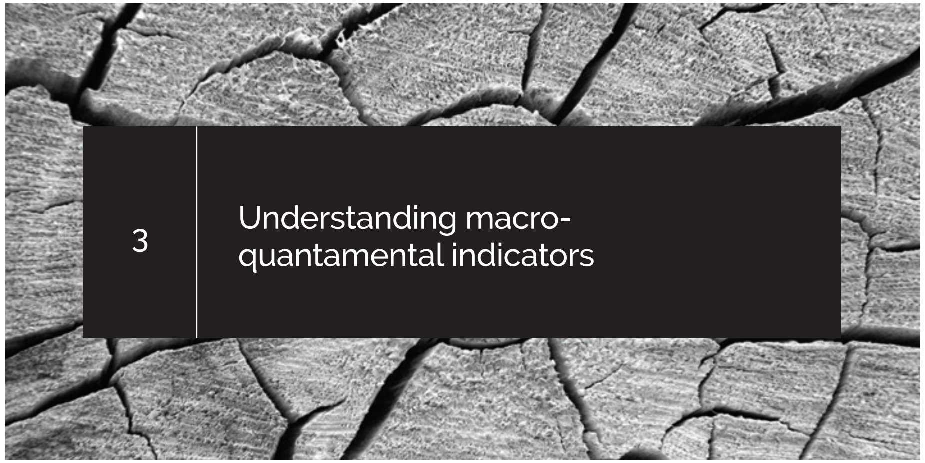
Endogenous market risk refers to uncertainty regarding the interaction of financial market participants, as opposed to uncertainty about traded assets' fundamental value. Endogenous market risk often manifests as feedback loops after some exogenous shock hits the market. An important type is setback risk, which refers to the asymmetry of the upside and downside potential of a trade that arises from market positioning. Setback risk is a proclivity to incur outsized mark-to-market losses even if the fundamental value proposition of the trade remains perfectly valid. Related macro factors typically measure the positioning or "crowdedness" in a trade as well as the probability that investors will exit the trade in the near term (view Section 5.4: Endogenous market risk[30]).

Figure 2.2: Groups of quantamental factors

Importantly, these three types of indicators are complementary, not competing. Indeed, powerful trading factors can be built on combinations of the above principal indicators. Thus, a price-value gap often arises as a consequence of implicit subsidies, meaning that the subsidized asset becomes overpriced for a reason. Also, typically setback risks arise alongside subsidies due to positioning, causing sudden large losses to subsidy receivers.



> “
>
> ...because information is costly, prices cannot perfectly reflect the information which is available, since if it did, those who spent resources to obtain it would receive no compensation.
>
> Grossman and Stiglitz



3 Understanding macro-quantamental indicators

A quantamental indicator is a metric that integrates quantitative and fundamental analysis to enhance investment decisions, such as equity valuation ratios or real interest rates. A crucial characteristic of a quantamental indicator is its point-in-time information state. It assigns values based on when the information became publicly available, not when the underlying events occurred. More specifically, a macro-quantamental indicator is a time series of relevant macro-economic information states designed for the development and back-testing of financial market trading strategies. Macro-quantamental indicators are a transformative technology for asset management and should not be confused with standard macroeconomic indicators or traditional macro trading signals. Macro-quantamental signals allow systematic trading to become more informed and make prices more “anchored” in economic reality, while reducing development costs.

What are macro-quantamental indicators

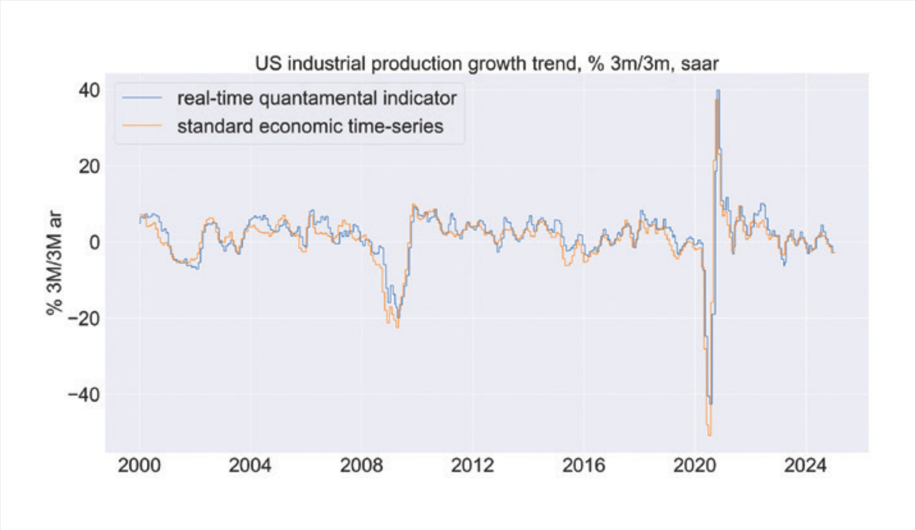
Macro-quantamental indicators are time series of macroeconomic information states designed for the development and backtesting of financial markets trading strategies[1].

– The term **"macro-quantamental"** generally refers to data that directly inform on the activity, balance sheets, and sentiment of various parts of an economy. This distinguishes it from market data, which dominates algorithmic trading, because they are timely and easily accessible. Market data may also relate to economic fundamentals, but only indirectly so and they are subject to many other influences, such as liquidity and risk aversion.

– Values are always **public information states** of the latest instance of a measure, such as GDP growth, earnings ratios, or real interest rates, as observed in real-time. This means that quantamental indicators are calculated based on data vintages, i.e., time sequences of full data histories. The recorded history of economic development changes for various reasons. Data are being revised by the source, seasonal and calendar adjustment factors are re-estimated, models used for nowcasting change, and conventions of the calculations of indicators evolve. Through the use of vintages, one can replicate what the market knew at a point in time in the past and, thereby, prevent any look-ahead bias in the development and evaluation of trading strategies. Beyond point-in-time values, the data of a good quantamental system include other helpful particulars, such as publication lags and the accuracy of replicating the historical information status.

Quantamental indicators typically carry the same name as standard economic data series. However, due to the point-in-time principle, values assigned to specific time periods are generally different. Figure 3.1 shows differences in point-in-time and standard time series of industrial production growth in the U.S. and Sweden. While the patterns of both types of series can be similar, the exact values differ and sometimes dramatically so.

As a result, backtests and statistical analyses based on standard economic data series can be grossly misleading. Two types of errors can arise from using standard economic series (or inferior point-in-time proxies) to detect valid trading factors. The first type is a "false positive" that detects a predictive relation when there is none. This typically happens when data are heavily revised with hindsight to fit past experiences. The second type is a "false negative" that misses a predictive relation when there has been one. This typically happens when data is followed avidly by markets in real-time but later revised, so that original effects are hidden.



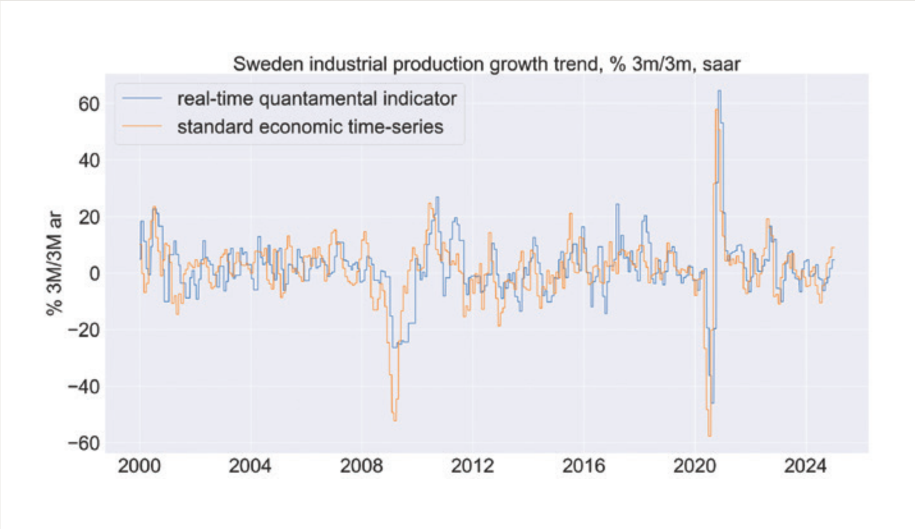


Figure 3.1: Example: Standard economic time series of production trends versus quantamental series

CONTENTS

Enhancement of the feature space of macro trading factors

Quantamental indicators **broaden the scope** of easily backtestable and tradable macro factors for investment strategies. At present, the vast majority of algorithmic strategies focus on market data, such as prices, returns, carry, flows, and maybe some alternative real-time data. In their basic form, quantamental indicators are like 'Lego' blocks that individually capture many relevant aspects of the economic environment, such as growth, inflation, profitability, or financial risks. Since all these "blocks" are available in the same point-in-time format, they can easily be combined and aggregated into a fully-fledged plausible trading signal. For example, excess inflation, consumption growth and employment growth can be added up to give an "overheating signal" for fixed-income and equity markets. Moreover, factors or signals can be calculated simultaneously across different countries, allowing testing and trading across a range of eligible markets. While the quantamental indicators or blocks are becoming more widely available, the construction of signals remains proprietary to the asset manager. Principally, every systematic relationship between economic states and developments and subsequent asset returns can be tested and implemented as a trading signal.

Information costs reduction

Readily available quantamental indicators **reduce data preparation and strategy development costs through scale effects**. They spread the investment of low-level data wrangling and codifying fundamental domain know-how across financial institutions. For individual managers, the development of trading strategies that use fundamentals becomes much more economical. Access to the system removes expenses for data preparation and reduces development time. It also centralizes curation and common-sense oversight. This allows investment managers to focus on their core strengths: the development of investment strategies or trading ideas and capital allocation. Most importantly, standardized quantamental indicators **reduce moral hazard**. Normally, if the production of indicators is a lengthy and expensive proprietary project, developers have a strong temptation to "make their project work" and to salvage any failed proposition through flexible interpretation and effective data mining. Simply put, placing the time and investment in macro-quantamental indicators on a single analyst or research group creates incentives to develop unprofitable trading strategies.

Figure 3.2: Why quantamental indicators add investor value

Why do quantamental indicators add investor value?

Quantamental indicators increase trading profits for two simple reasons: (view Figure 3.2)

– First, they greatly enhance the feature space for the construction and evaluation of systematic macro trading factors by allowing economic information to be used like price data.
– Second, they drastically reduce costs and development time of proprietary trading strategies with fundamental macro content.

The economic value of enhancing portfolio management through macro-quantamental trading factors at low cost is significant. Macrosynergy has demonstrated the predictive power and stylized PnL value of a range of plausible signals. Notably, the correlation between conceptually distinct macro-quantamental strategies has remained low over the past decades, owing to the differences in signals and the broad range of asset classes and contracts that can be traded with such signals (view Figure 3.3).

For 35 macro-quantamental strategies available on the Macrosynergy Quantamental Academy as of December 2024 across fixed income, equity, FX, credit, and commodities, the average Pearson correlation has been close to zero. Due to this diversification, a simple equally weighted average of these strategies, weighted by past volatility and rebalanced monthly, would have generated a high-Sharpe PnL with minimal seasonality and modest correlation to market benchmarks (view Figure 3.4).

Implications of two-dimensional underlying datasets

Macro quantamental indicators simply **align measurements of economic events with their lifespan** as the latest available information of its type. For instance, measurements of economic flows, such as production or sales, for a given month are associated with the time span from their release date up to but not including the date they become obsolete. Data becomes obsolete due to revisions or newly released periods. Quantamental indicators always represent the concurrent knowledge of a fully-informed investor.

This means that everyone actually considered or used the information in real time. The real-time date principle implies that quantamental indicators are principally **based on a two-dimensional data set** (view Table 1.1 on page 9).

– The first dimension is the timeline of **real-time dates**. It marks the progression of the market's information state.
– The second dimension is the timeline of **observation dates**. It describes the history of an indicator for a specific information state.

For any given real-time date, an indicator is calculated based on the full information state, typically a time series that may be based on other time series and estimates that would be available at or before the real-time date. This information state-contingent time series is called a **data vintage**.

The two-dimensional structure of the data means that unlike regular time series quantamental indicators convey information on two types of changes: **changes in**

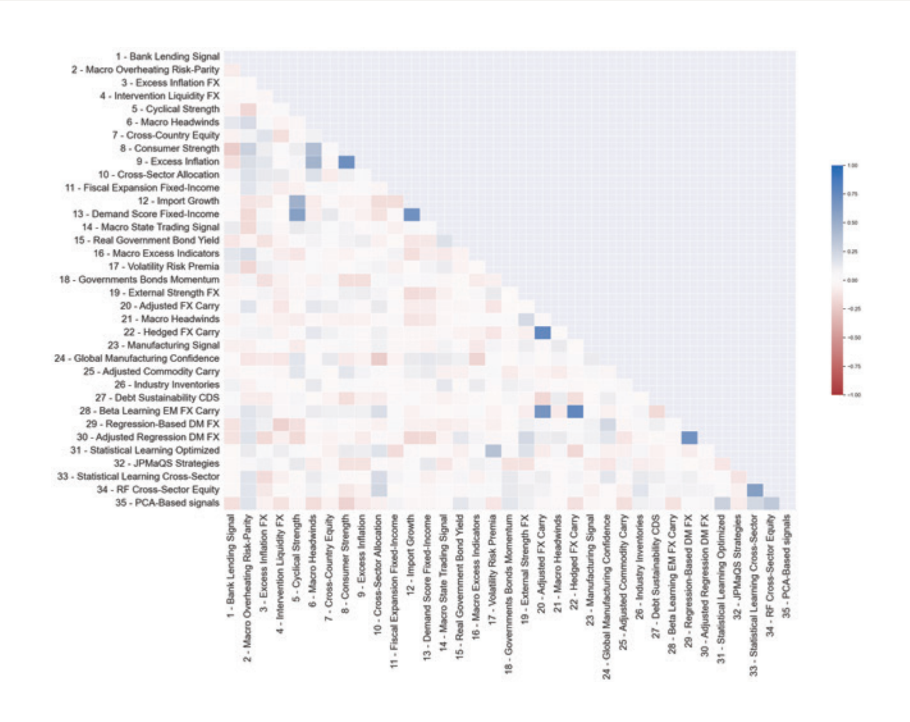


Figure 3.3: Monthly returns correlation for the main macro-quantamental strategies, 2000-2024 (Nov)

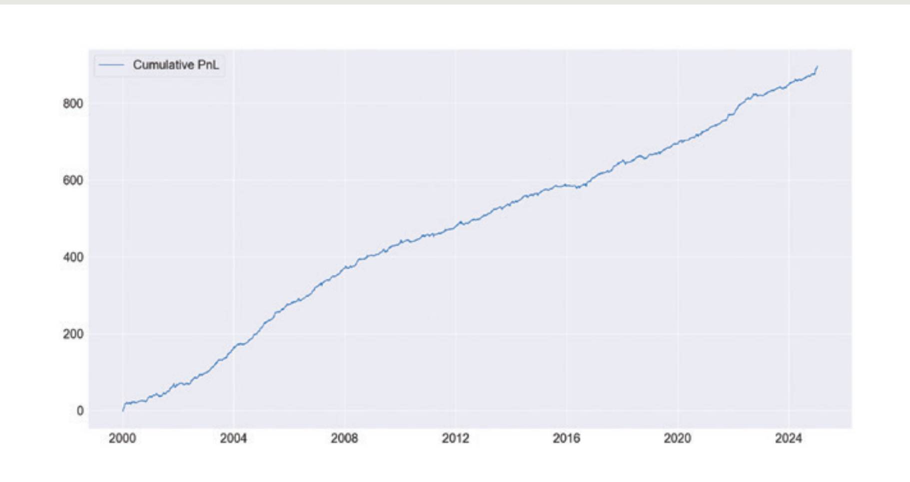


Figure 3.4: Naive PnL for the portfolio of macro-quantamental strategies, 2000-2024 (Nov)

reported values and reported changes in values. The time series of the quantamental indicator itself shows changes in reports arising from updates in the market's information state. By contrast, quantamental indicators of changes are reported dynamics based on the latest information state alone. This implies that a transformation (such as % change) of a quantamental indicator is not the same as a quantamental indicator of a transformation. The former operates on the first dimension (real-time dates), while the latter operates on the second dimension (observation dates).

A data vintage is an instance of a complete available time series associated with a real-time period. Conceptually, vintages are complete past states of information or "time series of time series". They come about through data revision, data extension, and re-estimation of the parameters of the underlying model. Vintages allow replicating what markets knew at any day in recent history, which is critical for backtesting algorithmic strategies. Disregarding vintages leads to survivorship and look-ahead biases in evaluating trading ideas.

The vintages-of-vintages paradox: why historic point-in-time series change

An inconvenient truth

Conceptually, all quantamental indicators are based on vintages, i.e., estimates of time series as they were available on the date of their timestamp. If all information was pristine, generated by a "time machine" that allowed to go back to each day and check what market participants found on their databases, the history of indicators should never change.

However, in practice, indicators and underlying vintages do change, sometimes even market-related data. This is inconvenient insofar as analyses based on these indicators change as well. Typically, these changes are tiny. However, changing backtests are principally disconcerting, and actual live trading decisions may need to be reviewed if changes are material.

Why point-in-time data evolve

Changes in past data vintages occur for three basic reasons:

Convergence

Quantamental systems should continuously ingest new information, albeit “new” here refers to older or more accurate historical records. Thus, the macro-quantamental history gradually converges towards a closer replication of the past. Standard parts of this evolution include the retrieval of older original vintages that supersede estimated ones, the discovery of a better vintage archive, or the switch to a better process to estimate older vintages. Also, sometimes more accurate release dates become available. Vintage changes due to convergence are desirable as they improve the quality of indicators. Convergence is a process that will go on for a long time, particularly when older vintages that are not available in electronic format are added.

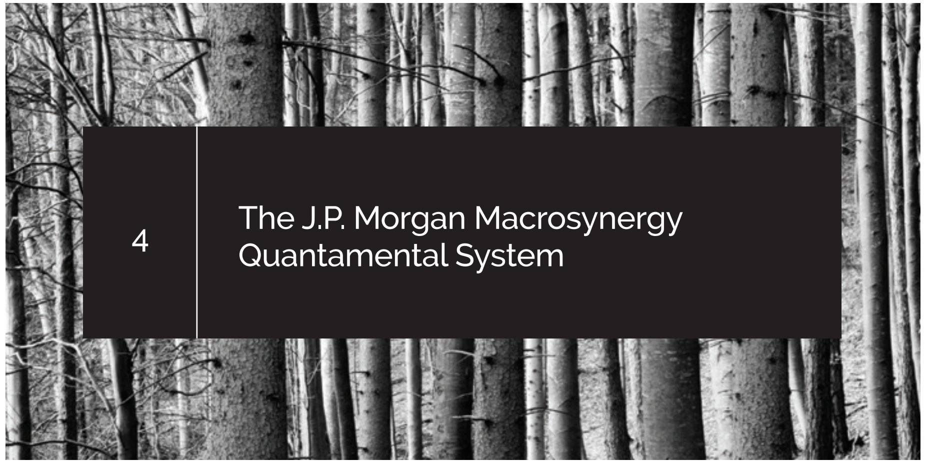
Corrections

Quantamental systems rely on vintage archives from many sources. Unfortunately, few people rigorously review the archives, and hence, curation is minimal. Data errors are regularly discovered, triggering changes in the electronic archives underlying the data warehouse. These changes are desirable, but it is possible that at times “new and improved” data sources have unexpected faults.

Fixes

Quantamental system code continuously evolves with a focus on optimization and improvement in data quality. If errors are discovered, they are fixed as soon as possible. Related changes in history may reveal inaccuracies in the system, but there must always be a commitment to providing the best quality at each point in time.

Figure 3.5: Reasons for the changes in past data vintages



4 The J.P. Morgan Macrosynergy Quantamental System

The J.P. Morgan Macrosynergy Quantamental System, or JPMaQS, is a powerful proprietary data and content service, built collaboratively by J.P. Morgan and Macrosynergy, that makes it easy to use quantitative -fundamental (“quantamental”) information for the development, backtesting and trading of algorithmic strategies, as well as for enhancing discretionary trading support tools.

J.P.Morgan + MACROSYNERGY

JPMaQS tracks a wide range of macroeconomic concepts such as economic growth, inflation, and external balance sheets, transforming them into daily point-in-time macroeconomic quantamental indicators. As of December 2024, JPMaQS processes over 1 billion raw data points, cleaning and refining them into over 35 million high-quality vintages to generate nearly 19,000 macro-quantamental indicators - the “building blocks” for developing trading signals and systematic strategies. New data and datasets are continually added to enhance this process. JPMaQS indicators offer an information advantage on macro factors across global fixed income, foreign exchange, equity, credit, and commodity markets. They also save costs compared to the alternative of building clean real-time macro data series in-house. Though JPMaQS is a premium and paid data service, the license fee is a fraction of the cost required to source, clean, and manage such data independently.

"JPMaQS allows research analysts, quants and portfolio managers to obtain the best possible information about the state of an economy at the time at which it was available. This means higher quality backtesting."
—Luis Oganes, Managing Director, Head of Global Macro Research, J.P. Morgan

Historically, macro-quantamental information has come in formats that were too messy to use for trading. Publication timestamps have been disregarded and forgotten; history has been compromised by revisions; models have been applied with hindsight; and data records regularly suffer from missing observations, value errors, undocumented distortions, and structural breaks. All this explains why most trading programs prefer market data. Fortunately, JPMaQS provides a solution for all these data format problems that stands to benefit all market participants.

– The term information state refers to the state of public knowledge of the latest instance of a measure, such as GDP growth, earnings ratios or real interest rates, as observed in real-time at a daily frequency. Moreover, the information here includes other helpful particulars, such as publication lags and purity of the replication of the historical information status. All of this information is geared towards helping professionals to build and evaluate trading strategies.
– JPMaQS builds a bridge between domain knowledge in the fundamental economic space and data science for trading strategies.

Key issues

- Even good data are usually one step removed from reality
- Formats are unwieldy and mismatched - very difficult to train a model
- Little standardization. Example: inflation indicators can be defined differently
- Expensive inputs - high fixed-costs in processing
- Revisionist history. Quant investing requires actual historical information state of the market

Implications

- Unrealized alpha
- Inaccurate, out-of-date models for back-testing
- Suboptimal information for investment decisions
- Broad market inefficiency
- High costs of trading strategy development
- Individual asset managers are challenged to do this themselves because of the scale, expense, and time constraints

Figure 4.1: Key issues and implications of using fundamental macro-economic data

Why does JPMaQS reduce costs?

JPMaQS makes macro-quantamental information affordable through scale effects. The system centralizes high-quality data wrangling and specialized macroeconomic know-how. Thereby, JPMaQS spreads the costs of low-level data wrangling and codifying fundamental domain know-how across a range of institutions. For individual managers, the development of trading strategies that use fundamentals becomes much more economical. In particular, access to the system drastically cuts research expenses and reduces development time. This allows focusing on the actual strengths of an asset manager: the development of investment strategies or trading ideas. JPMaQS also reduces harmful research biases: if the production of indicators is a lengthy and expensive proprietary project, there is a strong incentive to show some positive backtests simply to justify the effort.

Practically, JPMaQS delivers the following key services that would be very costly to the individual investment manager level (view Figure 4.2):

Quick & easy access to tradable data

Quantamental indicators come directly in a format that is required for developing and backtesting trading strategies. They are daily frequency, approximately point-in-time, and in a consistent form across countries. A single type of indicator, say a growth estimate, can be downloaded via a standard API in panel format. A panel here is a set of similar time series across various markets or countries, supporting diversification and relative value strategies.

Thorough documentation

Quantamental indicators come with comprehensive documentation. Trading strategies based on fundamentals hinge on an understanding of what the data really means. JPMaQS builds a bridge between domain knowledge of asset fundamentals and the deployment of data science in investment. Documentation notebooks provide a concise explanation and descriptive summary of each quantamental category from the angle of strategy builders. It also includes hints and links to research that document the value of the category for trading.

Expert curation and quality control

The system comes with quality control. JPMaQS benefits from common-sense oversight, embedded expert judgment, and added research. The wider JPMaQS team reviews and performs exploratory research on the quantamental themes. No system can eliminate all data problems, but JPMaQS is designed so that most issues are tracked down and resolved over time.

Generic returns for backtesting

For swift, efficient evaluation of strategy ideas, JPMaQS also contains a range of generic macro returns across asset classes and positioning conventions, including volatility targeting and hedging. While generic returns do not simulate exact PnLs, they usually reveal if a strategy idea has value and, thus, help developers to be more creative and identify opportunities faster.

Figure 4.2: JPMaQS key services

CONTENTS

What does it take to build good quantamental indicators?

Beyond the management of multi-dimensional underlying data series, the creation of quantamental indicators requires in-depth economic data knowledge, extensive data wrangling, applied econometrics and machine learning, and careful documentation. Also, the quality of quantamental indicators needs to be validated by accompanying research to ascertain their predictive power with respect to asset returns and suitability for the construction of related trading strategies (view Figure 4.3).

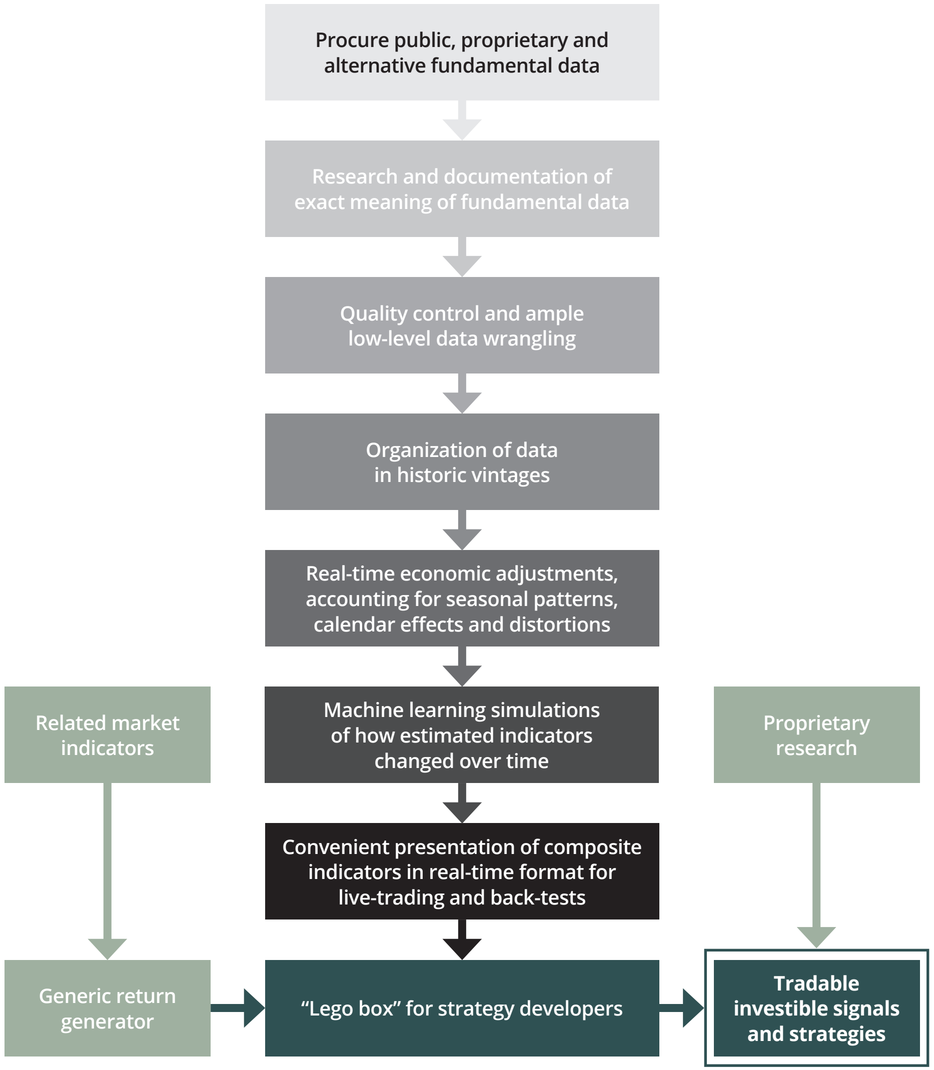


Figure 4.3: Steps in building good quantamental indicators

JPMaQS structure

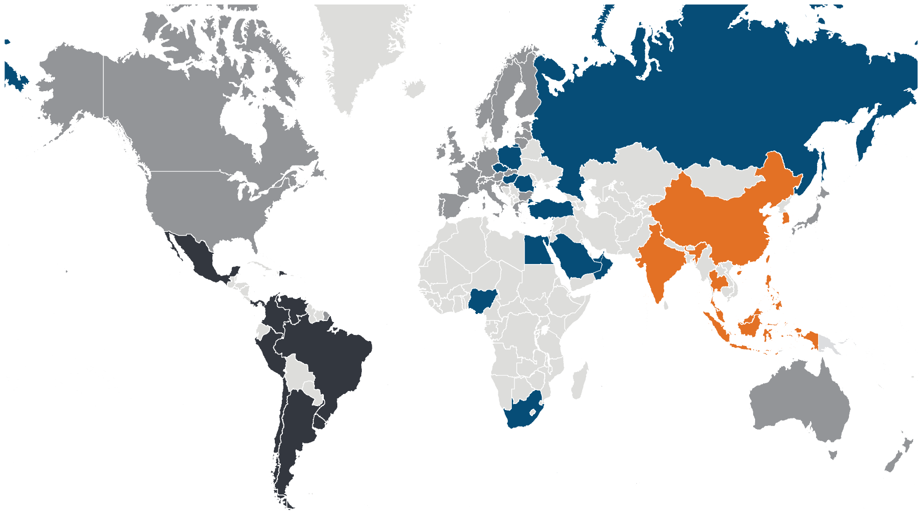
JPMaQS typically offers comparable quantamental indicators for a broad range of developed and emerging countries. These data panels are called quantamental categories. An example would be a short-term core CPI trend, whose information states are calculated for all available currency areas. Quantamental categories are then organized into conceptual category groups, such as consumer price trends or producer price trends. Finally, category groups are organized into the below six major themes (view also https://macrosynergy.com/academy/quantamental-indicators-on-jpmaqs[1]):

Economic trends	Macroeconomic trends are internationally comparable daily information states of the latest dynamics of economic aggregates, such as production, price indices, credit, and trade. Popular examples are real-time estimates of GDP growth, consumer price inflation, and employment changes. Macroeconomic trends are the largest set of category groups on JPMaQS, with a plausible and empirically proven predictive power for returns across asset classes.
Macro-economic balance sheets	Macroeconomic balance sheets are daily information states of important macro accounts, typically in the form of standard ratios. These accounts include high-level balance sheet positions of the government, the banking sector, the central bank, and international investment relations. Common examples include general government debt and deficits ratios to GDP, current account balances as % of GDP, and FX reserves as a ratio of international liabilities.
Financial conditions	Financial conditions are daily information states of economic and market factors that influence the ease of borrowing and raising capital in an economy. These typically are combinations of economic and market data and include metrics of real interest rates, real effective currency appreciation, terms-of-trade, credit growth, and central bank liquidity generation. Financial conditions are often among the most timely indicators of changes in economic development.
Shocks and risk measures	Shocks are daily information states of changes in uncertainty or risk aversion. Risk measures refer to daily information states of the magnitude of uncertainty and risk aversion. Unlike economic trends or balance sheets, these data are mainly based on market prices. However, they have macro implications. Examples include realized return volatility across asset classes, volatility risk premia, and tail risk premia.
Stylized trading factors	Trading factors are daily information states of composite indicators of economic and market information that are widely accepted as a valid basis for taking financial market positions. This theme is still at a primary stage, and the focus is mainly on types of cross-asset carry. Carry generally is defined as the return on an asset in a state where all market prices are unchanged. It requires the consideration of macro estimates, such as forward earnings growth and inflation.
Generic returns	Generic returns provide approximate daily profit and loss series' of positions in stylized contracts as a percentage of notional or risk capital. They are available for a range of asset classes, including interest rate swaps, government bonds, FX forwards, equity index futures, commodity futures, and some CDS indices. Many types of generic returns also include returns on volatility-targeted and hedged positions.

Figure 4.4: JPMaQS: Indicator themes

CONTENTS

JPMaQS geographical coverage



Dev markets	7,305	EMEA & SOAF	3,909	Asia	3,653	Latin America	2,146
Australia	600	Bahrain	7	China	444	Argentina	12
Canada	521	Czech Republic	429	Hong Kong	235	Brazil	418
Euro Area	518	Egypt	28	India	375	Chile	424
France	331	Hungary	423	Indonesia	396	Colombia	405
Germany	355	Israel	520	Malaysia	406	Dom Republic	25
Italy	336	Nigeria	26	Philippines	362	Mexico	427
Japan	612	Oman	13	Singapore	475	Panama	18
Netherlands	219	Poland	454	South Korea	436	Peru	383
New Zealand	573	Qatar	12	Taiwan	367	Uruguay	25
Norway	518	Romania	387	Thailand	413	Venezuela	9
Spain	336	Russia	410				
Sweden	541	Saudi Arabia	13				
Switzerland	528	Serbia	28				
United Kingdom	634	South Africa	441				
United States	683	Turkey	450				
		UAE	12				

Figure 4.5: JPMaQS geographical coverage (as of October 2024). Totals include indicators for Commodities and Global assets.

Detailed information and documentation on JPMaQS are available on J.P. Morgan Markets, and macro-quantamental indicators can be accessed through the DataQuery API, which provides simple and fast authentication via OAuth[2].

5 Value generation based on quantamental indicators

Macro-quantamental information creates trading value through various strategy principles. Generally, financial markets are not macro information efficient. The principal obstacles to information efficiency are costs and external effects (view The macro information inefficiency of financial markets[1]). Since price relevant information comes at a cost, it will only be procured to the extent that inefficient markets allow translating it into sufficient returns. Acknowledging the cost-return trade-off, the rational inattention theory provides a model of how market participants manage their attention scarcity (view Rational inattention and trading strategies[2]). Rational inattention explains why agents pay disproportionate attention to popular variables, simplify the world into a small set of indicators, pay more attention in times of uncertainty, and limit their range of actions. (view Value generation based on quantamental factors[3]).

5.1 Using macro trends

Macroeconomic trends predict asset returns for two principal reasons:

– They affect investors' attitudes toward risk and
– influence the expected risk-neutral payoff of a financial contract.

The market impact of macroeconomic trends is typically more pronounced over longer horizons (such as months) than over shorter horizons (such as days). The relevance and predictive power of point-in-time macro trends have been demonstrated in applied research for all major asset classes: fixed income, foreign exchange, equities, commodities, credit derivatives, and cross-asset return correlation. The alignment of macroeconomic trend information and trading positions is often simple and straightforward (view Macro Trends[4]).

The importance of macro trends

Why macroeconomic trends matter

Generally, all market prices are part of an economic equilibrium. More specifically, macroeconomic trends influence asset prices for two reasons: They affect investors' attitudes toward risk and shape the expected risk-neutral payoff of a financial contract.

– Risk aversion rises in recessions due to a focus on preserving limited resources. Standard economic theory proposes that the marginal utility of income increases as income falls. When household income declines and fear of unemployment rises, each incremental dollar becomes more valuable. The fear becomes more acute near the lower limits of living. Similar aversion to breaking downside thresholds can be observed in the financial industry. There is even a special concept of "loss aversion," which is not the same as risk aversion (view How loss aversion increases market volatility and predicts returns[5]) because the aversion is disproportionate toward drawdowns below a threshold.
– The effects of macroeconomic trends on risk-neutral expected payoffs of securities are ubiquitous and often obvious. For example, inflation directly impacts the real return of nominal fixed-income securities; as inflation rises, the real purchasing power of fixed-income payments decreases. Similarly, macroeconomic trends such as economic growth and relative price-wage trends influence the earnings prospects of stocks. Also, financial conditions affect the default risk of credit. External balances and relative prices of goods and services matter for exchange rate dynamics.

The importance of macroeconomic information is recognized by many investors. They monitor economic data releases and employ economists for deeper analyses. Empirical studies show that bond and equity markets are more likely to post large moves on days of key data releases than on other days (view The short-term effects of U.S. economic data releases[6]). However, the influence of economic data on market price changes tends to be stronger over longer time horizons. This is because macroeconomic developments and their effects are often more persistent than non-fundamental factors, such as market sentiment or order flows. Therefore, macroeconomic trends are a significant explanatory factor of medium to long-term price trends.

5. Value generation based on quantamental indicators

– In the **fixed-income** market, empirical work has shown that point-in-time information state changes in several key economic areas have been significant predictors for duration returns. Academic work suggested that deviations of major economic data from analyst expectations can explain more than a third of quarterly bond price fluctuations in the U.S. (view Macroeconomic news and bond price trends[7]). By contrast, daily data surprises explain only 10% of market fluctuations. Medium-term returns of government bonds seem to be predictable through nowcasted economic growth, excess inflation relative to the target (view Excess inflation and asset class returns[8]), excess domestic macroeconomic demand (view Macro demand-based rates strategies[9]), nominal import growth (view Merchandise import as predictor of duration returns[10]), and measures of financial market tail risk (view U.S. Treasuries: decomposing the yield curve and predicting returns[11]). Over the longer term, bond yields seem to move almost one-to-one with expected inflation and the estimated equilibrium short-term real interest rate (Treasury yield curve and macro trends[12]). Equilibrium theory helps explain how macroeconomic trends and expectations for future short-term interest rates shape the yield curve (view Equilibrium theory of Treasury yields[13]). Stable components in GDP growth and inflation drive long-term yield trends. Transitory deviations of GDP growth and inflation cause cyclical movements in yield curves. Moreover, there is evidence that bond returns contain significant risk premia for regime changes related to economic growth and inflation in an economy (view A model for bond risk premia and the macroeconomy[14]). Moreover, research claims that a single fundamental divergence may explain most of the decline in equilibrium real interest rates from the 1980s to the 2010s. On the one hand, the propensity to save surged due to demographic changes (view The demographic compression of interest rates[15]) rising inequality of wealth, and the reserve accumulation of emerging market central banks. On the other hand, investment spending was reduced by cheapening capital goods and declining government activity (view The secular decline in the global equilibrium real interest rate[16]).

– In the **foreign exchange space**, theory and evidence support a positive relationship between growth differentials and FX forward returns (view Economic growth and FX forward returns[17]) and a close link between relative industry cycles and exchange rate dynamics (view FX trading strategies based on output gaps[18]). Currencies of countries in a strong cyclical position are expected to appreciate against those in a weak position. Also, macroeconomic indicators of competitiveness of currency areas are significant predictors of FX forward returns and a solid basis for pure macro(economic) trading strategies (view Pure macro FX strategies: the benefits of double diversification[19]). Standard FX carry signals can be significantly improved by enhancing them with information on economic performance, leading to the advanced concepts of "modified real carry" and "balanced real carry" (view Modified and balanced FX carry[20]). Similarly, standard FX trend following can be improved by considering macro headwinds (view FX trend following and macro headwinds[21]). Deviations of currency values from their

CONTENTS ⟶

medium-term equilibrium give rise to multi-year exchange rate trends. Over time, exchange rates between areas of similar economic development have been observed to revert to their mean values, and adjustments have occurred mainly through changes in the nominal exchange rate. (view A simple rule for exchange rate trends[22]). External balances, which describe transactions between residents and non-residents of a currency area, also predict exchange rates and FX returns. Modern international capital flows are mainly about financing rather than goods transactions. The patterns and risks associated with international capital flows and financial shocks shape FX return dynamics (view Understanding international capital flows and shocks[23]). For example, a large negative international investment position of a currency area encourages FX hedging against that currency, particularly in times of turmoil, and hence positive but pro-cyclical FX returns (view External imbalances and FX returns[24]).

– As to **equity** markets, research supports a close link between macroeconomic developments and the two key components of stock valuation: earnings and discount factors. As a result, research has found many applications of macro indicators for the prediction of broad equity returns:

- When stock prices increase, they contribute to the growth of household wealth and create favorable conditions for corporate investment. This, in turn, leads to a rise in aggregate spending, tighter labor markets, and potentially inflationary pressure, all of which are headwinds for positive equity market trends. Therefore, broad macro trends help predict market trends' sustainability (view Equity trend following and macro headwinds[25]). For example, stronger consumer spending and tighter labor markets undermine monetary policy support and typically indicate a shift in national income from corporate to households. Private consumption strength has negatively predicted local-currency equity returns in the past and has been valuable for the timing of equity market turning points (view Equity market timing: the value of consumption data[26]).

- Inflation is another valuable equity trading signal. In past decades, even the simplest inflation metrics have served as warning signals at the outset of large market drawdowns and as a heads-up for opportunities before recoveries. The evident predictive power of inflation for country equity indices has broad implications for using real-time CPI metrics in equity portfolio management. (view Inflation and equity markets[27]). Also, a downshift in expected inflation can have multiple effects on equity markets: it raises average company valuation ratios, such as price-earnings ratios and credit default risk, at the same time. This combination of higher valuation ratios and increased credit risk can contribute to a relative asset class trend, where investors shift their preferences towards equities compared to other asset classes (view Equity values and credit spreads: the inflation effect[28]).

- Improving bank lending conditions bolster aggregate demand in the economy and the creation of leverage. Both augur well for corporate profitability and forthcoming earnings reports. Indeed, signs of strengthening credit supply or demand in bank lending surveys have positively predicted equity returns in past decades (view Equity versus fixed income: the predictive power of bank surveys[29]).

- Intervention liquidity expansion is a helpful predictor of relative equity market performance across different currency areas (view Intervention liquidity[30]). This indicator captures the monetary base expansion resulting from central bank open market operations in FX and fixed-income markets. Equity markets with more expansionary operations have an advantage over those with less liquidity supply.

- Measures of macroeconomic uncertainty, i.e., unpredictable disturbances in economic activity, serve as predictors of equity market volatility (view Macro uncertainty as predictor of market volatility[31]).

- Macroeconomic trends also affect the relative performance of sectoral equity indices. For example, the state of the business cycle, relative price trends, or financial conditions drive divergences in business conditions. Empirical evidence exists of sizable value generation through macro factor-based sector allocation across international equity markets (view Macro factors and sectoral equity allocation[32]).

- Finally, the prices of equity factor portfolios seem anchored by the macro-economy in the long run. This implies predictability of equity factor performance going forward (view Equity factor timing with macro trends[33]) and explains why macroeconomic indicators can be used for equity factor timing, i.e., when to receive and pay alternative non-directional risk premia (view Factor timing[34]). Put simply, macroeconomic conditions may influence the probability that a specific investment factor will yield good returns. This is consistent with the evidence of momentum in various equity factor strategies (view Factor momentum: a brief introduction[35]), i.e., past equity factor returns have historically predicted future returns. Moreover, some research shows that macroeconomic factors, such as short-term interest rates, help predict the timing of exposure to equity convexity, i.e., stocks whose elasticity to the market return is curved upward and that outperform in large market moves (view Equity convexity and gamma strategies[36]).

– In **commodity markets**, macroeconomic trends influence mainly industrial demand and financial investor preferences. There is strong evidence that macroeconomic data support predictions of short-term energy market trends (view Forecasting energy markets with macro data[37]). Valid macro indicators include shipping costs, industrial production measures, non-energy industrial commodity prices, transportation data, weather data, financial conditions indices, and geopolitical uncertainty measures. Macroeconomic indicators of industry sentiment, production, and inventory growth have also helped predict base metal futures returns (view Predicting base metal futures returns with economic data[38]). Changes in manufacturing business confidence can be aggregated by industry size across all major economies to give a powerful directional signal of global demand for metals and energy (view Business sentiment and commodity future returns[39]). Meanwhile, the big cycles in some raw material prices have been driven mainly by "demand shocks," which seem to be related to global macroeconomic changes and have had persistent effects for 10 years or more (view The drivers of commodity cycles[40]). Precious metals prices have a long-term equilibrium relationship with consumer prices and are natural candidates for hedges against inflationary monetary policy (view Inflation and precious metal prices[41]).

– In **credit markets**, macroeconomic trends influence attitudes toward default risk and actual default probabilities. When systemic stress is high, investors require greater compensation for exposure to corporate default risk. This explains why measures of systemic macro default risk predict low-grade bond returns negatively (view Tracking systematic default risk[42]). Selling protection through credit default swaps (CDS) is akin to writing put options on sovereign default. In sovereign CDS markets, default risk depends critically on sovereign debt dynamics. There is strong evidence of a negative relation between increases in predicted debt ratios (under current market conditions) and CDS returns. (view Sovereign debt sustainability and CDS returns[43]).

– The **correlation across asset markets** also depends on macro factors. The most prominent example is the correlation between equity and bond returns. Economic policy is a key macro force behind it (view The macro forces behind equity-bond price correlation[44]). In an active monetary policy regime, where central bank rates respond disproportionately to inflation changes, the influence of technology (supply) shocks dominates markets, and the correlation turns positive. In a fiscal policy regime, where governments use debt financing to manage the economy, the influence of investment (financial) shocks dominates, and the correlation turns negative.

Economic shocks have more powerful market effects if they change long-term expectations. Thus, a key factor of economic impact is whether long-term expectations are "anchored" or not. For example, persistent undershooting of inflation targets in the developed world has made long-term inflation expectations more dubious and susceptible to short-term inflation trends. This "de-anchoring" can be measured (view Understanding dollar shortages and related market dynamics[45]) through surveys and long-dated securities, providing valuable information on the consequences of price shocks for markets.

"Macroeconomic news has a persistent effect on bond yields, whereas the effect of non-fundamental factors is less persistent and it tends to average out when focusing on longer horizon changes."
—Altavilla, Gianonne, and Modugno, 2014

Aligning macro trends and market positions

The directional effect of economic change is often straightforward, following standard macroeconomic theory and market experience. For example, rising expected inflation and lower unemployment have historically translated into higher low-risk bond yields (view The fall of inflation compensation[46]). Also, swings in large commodity-intensive sectors, such as construction in China, have driven global prices for raw materials, such as base metals (view China housing and global base metal prices[47]). Furthermore, export price changes in "commodity countries" help explain and even predict their exchange rate dynamics (view Using commodity prices to predict exchange rates[48]).

However, many macroeconomic trends can also have multiple effects, which need to be disentangled. For example, expansionary financial conditions can be both beneficial and harmful for future equity market performance, depending on the trade-off between positive growth impact and elevated vulnerability. On these occasions, indicators must be modified, become parts of larger formulas, and be split into different parts. For example, financial conditions can be divided into short-term impulses, such as yield compression, and medium-term vulnerability, such as increased leverage (view How to use financial conditions indices[49]). Combinations of negative shocks and elevated vulnerability would then be clear negative signals for equity markets. Combinations of positive impulses and low vulnerability would be clear positive signals.

Global macro and market factors often obfuscate the relationship between country-specific macroeconomic trends and financial returns.

– For example, the value of a currency typically benefits from strengthening the underlying economy relative to other countries. However, almost all currencies are, to varying degrees, sensitive to changes in global markets and the exchange rates of the largest economies. To validate and trade relative economic trends, it is, therefore, useful to hedge against such global influences or set up positions relative to similar contracts or both. Empirical evidence suggests that global FX forwards can be hedged reliably against the largest part of global market influences (view Hedging FX trades against unwanted risk[50]).

– More generally, macro sensitivities are endemic in trading strategies, diluting alpha, undermining portfolio diversification, and distorting backtests. However, it is possible to immunize strategies through "beta learning," a statistical learning method that supports identifying appropriate models and hyperparameters and allows backtesting of hedged strategies without look-ahead bias (view How "beta learning" improves macro trading strategies[51]).

Sometimes, information regarding economic uncertainty can be as valuable as information on the economic direction. One can estimate economic uncertainty through various methods, such as keyword frequency in the news, relevant market volatility, and forecast dispersions. Such measures help to detect phases of popular fear or panic and complacency (view How to measure economic uncertainty[52]), both of which offer opportunities for professional investors. Indeed, composite measures suggest that uncertainty typically rises abruptly but subsides only gradually. Unsurprisingly, uncertainty about the economic and financial state, in general, has been conducive to higher volatility in market prices, including commodities (view The drivers of commodity price volatility[53]). Economic uncertainty can also affect directional trends. For example, there is evidence that uncertainty about external balances leads to the underperformance of currencies of economies with net capital imports (view FX returns and external balances[54]).

"So even if you're not a systematic trader, it's worth venturing into the world of statistical programming. It will make it easier to number crunch data and help you to make decisions quicker." —Saeed Amen

Best practices for tracking macro trends

Macro trend indicators

Since the range of available macro data is vast, they must inevitably be condensed into small manageable sets of meaningful indicators. Generally, a macro trend indicator can be defined as an updatable time series that represents a meaningful economic or financial trend, and that can be mapped to the performance of tradable assets or derivatives positions. There are three major sources of information for macro trend indicators:

- Economic data
- Financial market data
- Expert judgment

While these sources are often portrayed as competing investment principles, they are highly complementary. Economic data establish a direct link between investment and economic reality, market data inform on the state of financial markets and economic trends that are not (yet) incorporated in economic data, and expert judgment is critical for formulating stable theories and choosing the right data.

"In-sample evidence suggests that higher economic policy uncertainty leads to significant increases in market volatility. Out-of-sample findings show that incorporating economic policy uncertainty as an additional predictive variable into the existing volatility prediction models significantly improves the forecasting ability of these models." —Li Liu and Tao Zhang, 2015

Economic data

For all major economies, statistical offices publish wide arrays of economic data series, often with changing definitions, elaborate adjustments, multiple revisions, and occasional large distortions. Monitoring economic data consistently is tedious and expensive. Most professional investors find it easier to trade on data surprises than on actual macro trends. It is not uncommon for investment managers to consider an economic report only with respect to its presumed effect on other investors' expectations and positions and to subsequently forget its contents within hours of its release.

What makes monitoring economies difficult is that there is usually no single series that represents a broad macroeconomic trend on its own in a timely and consistent fashion. To begin with, conventional economic data are published with considerable lags, subject to frequent revisions, and often their true history is very hard to reconstruct for financial market backtesting. Moreover, many important types of macro information for markets are not produced by central agencies. For example, equilibrium real interest rates and long-term inflation trends are essential factors for fixed-income strategies (view Treasury yield curve and macro trends[55]). Yet neither of these is available as an official, reliable data series since such estimation requires judgment and macroeconomic modeling (view U.S. natural interest rate stuck at 0%: evidence and consequences[56]). Even apparently simple indicators, such as inflation trends, use a range of different data series at the same time, such as consumer price growth, "core" inflation measures, price surveys, wage increases, labor market conditions, household spending, exchange rates, and inflation derivatives in financial markets. In practice, the use of economic data for macro trading requires [1] producing special tradable economic data, [2] formulating a plausible and logical theory to create meaningful indicators, and [3] applying statistical methods.

Published economic data cannot be easily and directly plugged into systematic trading strategies. Unlike financial market data, which are intensively used for algorithmic and systematic trading, economic data come with several inconvenient features such as low frequency of updating, lack of point-in-time recording, and backward revisions. Therefore, economics statistics and other quantifiable information must be brought into a form that is suitable for systematic research. One can call this form tradable economic data (view Tradable economics[57]).

Theoretical structure establishes a plausible relation between the observed data and the conceived macroeconomic trend. This is opposite to data mining and requires that we set out a formula based on our understanding of the data and the economy before we explore the actual data.

– As a simple example, different sectoral production reports can be combined by adding them in accordance with the weight of the sectors in the economy.
– The monetary policy stance in a regime with sizable asset purchase programs can be estimated as a single "implied" short-term interest rate based on the actual short-term interest rate and the equivalent effect of compression of term premia, based on a yield curve factor model (view Monetary policy stance in one indicator[58]).
– As a more advanced example, we can extend measures of consumer price inflation by indicators of concurrent aggregate demand. This helps to distinguish between supply and demand shocks to prices, making it easier to judge whether a price pressure will last or not (view Forecasting inflation under globalisation[59]).
– Even modern academic macroeconomic theory can help. True, dynamic stochastic general equilibrium models are often too complex and ambiguous for practical insights. However, simplified static models of the New Keynesian type incorporate important features of dynamic models while still allowing us to analyze the effect of macro shocks on interest rates, exchange rates, and asset prices in simple diagrams (view Simple macroeconomics for trading[60] and Simple international macroeconomics for trading[61]).

Statistical methods become useful where our prior knowledge of data structure ends. They necessarily rely on the available data sample. With respect to economic trends, they can accomplish two major goals: dimension reduction and nowcasting.

CONTENTS

– **Dimension reduction** condenses the information content of a multitude of data series into a small manageable set of factors or functions. This reduction is important for forecasting with macro variables because many data series have only limited and highly correlated information content. (view Statistical remedies against macro information overload[62]).

– **Nowcasting** tracks a meaningful macroeconomic trend in a timely and consistent fashion. An important challenge for macro trend indicators is timeliness. Unlike financial market data, economic series have monthly or quarterly frequency, giving only 4 -12 observations per year. For example, GDP growth, the broadest measure of economic activity, is typically only published quarterly with one to three months delay. Hence, it is necessary to integrate lower and higher-frequency indicators and to make use of data releases with different time lags.

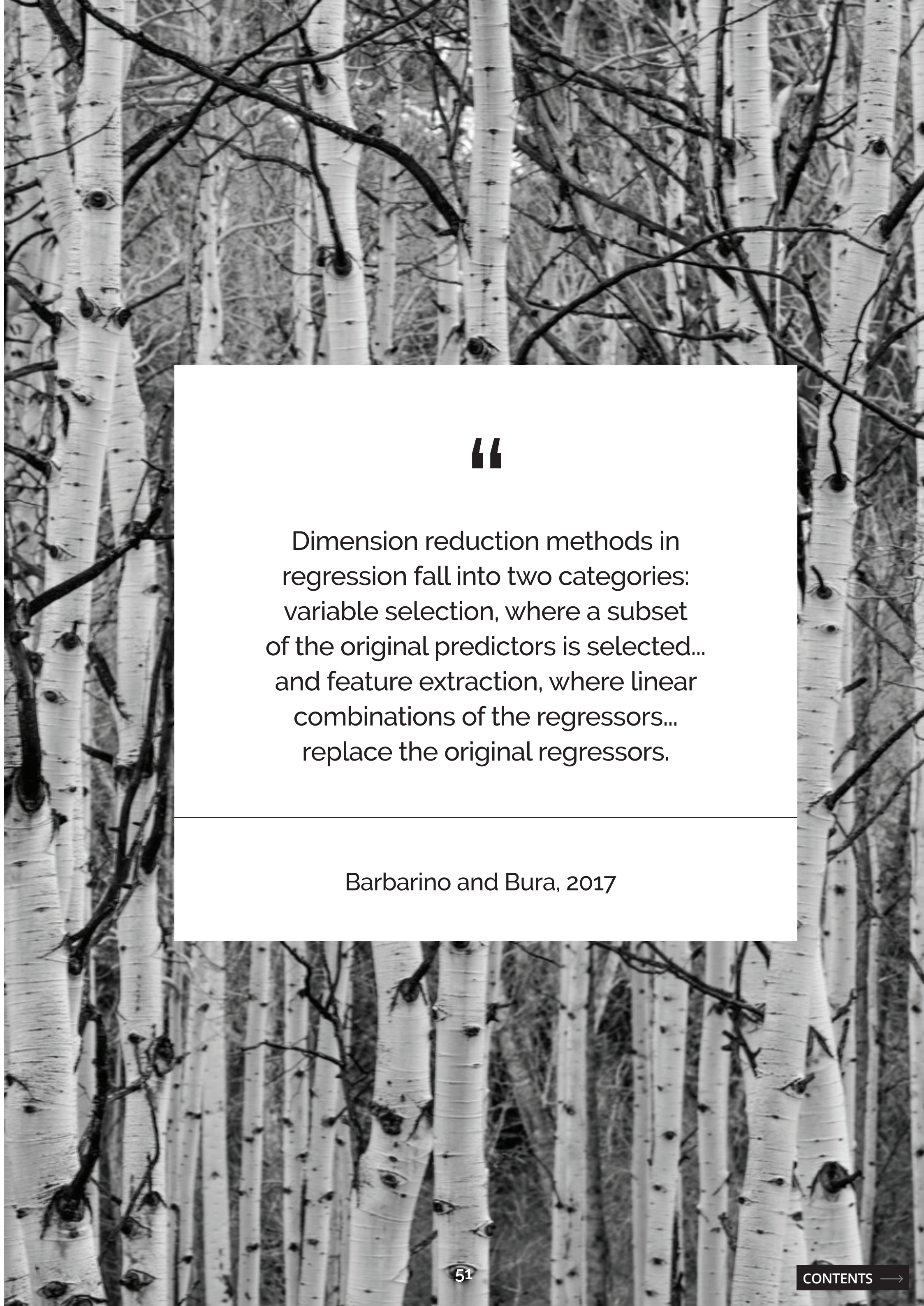
In recent years, dynamic factor models have become a popular method for both dimension reduction and nowcasting. Dynamic factor models extract the communal underlying factor behind timely economic reports and translate the information of many data series into a single underlying trend (view Nowcasting GDP growth[63] and Tracking trends in EM economies[64]). This single underlying trend is then interpreted conceptually, for example, as "broad economic growth" or "inflation expectations". Also, the financial conditions of an economy can be estimated by using dynamic factor models that distill a broad array of financial variables (view Building international financial conditions indices[65]).

It is often helpful to measure local macroeconomic trends from a global perspective. Just looking at domestic indicators is rarely appropriate in an integrated global economy. As a simple example, inflation trends have increasingly become a global phenomenon due to globalization and convergent monetary policy regimes. Over the past three decades, local inflation has typically been drifting towards global trends in the wake of deviations (view Forecasting inflation under globalisation[66]). As an example of the global effects of small-country shocks, "capital flow deflection" is a useful conceptual factor for emerging markets that stipulates that one country's capital inflow restrictions are likely to increase the inflows into other similar countries (view Understanding capital flow deflection[67]). In order to measure this effect, one needs to build a time series of capital controls in all major economies in order to distill the specific impact on a single currency.

"Dimension reduction methods in regression fall into two categories: variable selection, where a subset of the original predictors is selected... and feature extraction, where linear combinations of the regressors... replace the original regressors."
—Barbarino and Bura, 2017

Financial market data

Financial market data is often more readily available and at higher frequencies compared to macroeconomic data. Additionally, investment professionals are generally more familiar with financial market data and find it easier to interpret. However, extracting specific macro trend information content from financial data



"
Dimension reduction methods in regression fall into two categories: variable selection, where a subset of the original predictors is selected... and feature extraction, where linear combinations of the regressors... replace the original regressors.

Barbarino and Bura, 2017

can be challenging as a single price typically reflects the influence of many factors. Isolating the macroeconomic component from these factors requires theoretical modeling and statistical methods.

– A simple example would be to derive inflation expectations from breakeven inflation, as priced in the inflation swap markets. For this purpose, we must at least make an adjustment for the inflation risk premium embedded in the swaps contract, possibly by using the correlation of inflation swaps with broad market benchmarks (view Inflation: risk without premium[68]).
– Trends in industrial commodity prices are typically aligned with global demand, economic growth, and, ultimately, inflationary pressure. Since commodity prices are observable in real-time, they can predict related economic trends. And since most of these economic trends matter for interest rates, they help to forecast bond returns (view Commodity trends as predictors of bond returns[69]). More advanced information extraction would check whether rising commodity prices have coincided with upward or downward revisions to global industrial activity. This helps to distinguish between commodity supply and global demand shocks; these two can have very different implications for the exchange rate, equity, and rates markets (view The importance of differentiating types of oil price shocks[70]). Also, commodity-based terms-of-trade indicators are drivers and valid predictors of FX forward returns (view Terms of trade as FX trading signal[71]).

– Another intuitive source of information on perceived uncertainty is the futures curve of implied equity index volatility, particularly VIX (view VIX term structure as a trading signal[72]). This curve is shaped by the relation between present and future expected volatility and, hence, serves as an indicator of present complacency, in the form of a steep curve or panic, through an inverted curve.

– Bond and swap yields are a rich source of information. The level of real short-term rates is related to the monetary policy stance. The slope of the curve is related to expected future policy rates and risk premia. And the curvature of the term structure is naturally related to the expected “over-tightening” or “under-tightening” of monetary policy and, hence, is a valid trading signal for the foreign exchange market (view Using yield curve information for FX trading[73]). Moreover, the difference between government bond yields and swap yields, adjusted for credit risk, is often indicative of a “liquidity yield” or “convenience yield” of government bonds, i.e., non-pecuniary benefits that arise from high liquidity, suitability as collateral and eligibility as regulatory liquidity buffers. Such liquidity yields not only indicate long-term expected returns of the bonds themselves, but their changes also affect exchange rate dynamics in a similar manner as changes in interest rates (view Liquidity yields and FX[74]). For example, since the dollar exchange rate clears the market for safe dollar assets, increases in the convenience yield for these assets typically trigger an overshooting in the international value of the dollar (view Treasury basis and dollar overshooting[75]).

– Another simple and popular example is the measurement of monetary policy uncertainty through short-term rate derivatives. Policy uncertainty is a key component

of equity return volatility that improves predictions that are otherwise based on historical and implied equity volatility alone (view Policy rates and equity volatility[76]).

– The term premia in credit default swap curves are indicative of country’s financial risk. In particular, flattening or inversion of CDS curves is typically indicative of negative country-specific shocks (view CDS term premia and exchange rates[77]). Empirical research suggests that changes in CDS term premia have predicted exchange rate changes and local stock returns in the past.

– The USD exchange rate has become an important early indicator for U.S. and global credit conditions (view The dollar as barometer for credit market risk[78]). This is because a large share of corporate loans is regularly sold to mutual funds. In times of USD strength, credit funds typically experience outflows as the balance sheets of non-U.S. borrowers deteriorate, i.e., the weight of their USD debt increases relative to non-USD assets.

– Financial return volatility across asset classes is one of the most popular indicators for the quantity of risk and the aversion to risk. Implied volatility indices can be constructed across asset classes based on out-of-the-money call and put premia and can be used to extract forward-looking market information (view How to construct a bond volatility index and extract market information[79]). Realized volatility is typically calculated as the (annualized) standard deviation of returns over a period, usually from the close of one trading day to the close of the next. However, alternative useful concepts of volatility make use of open, close, high, and low prices and even trading volumes (view Six ways to estimate realized volatility[80]). Moreover, heterogeneous autoregressive models of realized volatility have become a popular standard for predicting volatility at various frequencies (view Predicting volatility with heterogeneous autoregressive models[81]). Moreover, equity and bond market volatility can be decomposed into persistent and transitory components by means of statistical methods. Plausibility and empirical research suggest that the persistent component of price volatility is associated with macroeconomic fundamentals.

This means that persistent volatility is an important signal itself and its sustainability depends on macroeconomic trends and events (view What traders can learn from market price volatility[82]). Meanwhile, the transitory component, if correctly identified, is more closely associated with market sentiment and can indicate mean-reverting price dynamics.

– An example that relies more on statistical estimation would be the measurement of non-conventional monetary policy shocks based on asset prices. For this, we can estimate changes in the first principal component of bond yields that are independent of policy rates and on monetary policy announcement dates. Non-conventional monetary policy shocks tend to have a profound and lasting impact on most asset markets (view Measuring non-conventional monetary policy surprises[83]).

A global perspective is probably more crucial for analyzing financial data than for economic data, particularly given the worldwide influence of U.S. financial markets. Here are some key points related to this perspective:

- Impact of U.S. monetary policy: Research has shown that shocks to U.S. monetary policy have a significant impact not only on the U.S. dollar exchange rates but also on foreign-currency risk premia more broadly. Changes in U.S. monetary policy can reverberate across global financial markets, affecting interest rates, asset prices, and investor sentiment in various countries (view Fed policy shocks and foreign currency risk premia[84]).

- Transmission of term premium shocks: Shocks to the term premium in longer-dated U.S. yields can have persistent subsequent effects on term premia in other global markets (view The global effects of a U.S. term premium shock[85]).

- Cross-asset class perspective: Different market participants and institutions specialize in different types of assets and information. Equity investors tend to focus more on corporate earnings prospects, while fixed-income investors pay greater attention to macroeconomic trends and monetary policy. Investment strategies in one market can often benefit from the information provided by another if one is familiar with "decoding" price signals quickly. For instance, equity markets have historically been more sluggish than bond markets in adjusting discount factors to shifts in relative country inflation (view Inflation differentials and equity returns[86]). Similarly, changes in the implied pace of future policy rates, as priced by fed funds futures, have in the past helped to predict equity returns (view Policy rates and equity returns: the "slope factor"[87]) and even the U.S. dollar exchange rate (view U.S. dollar exchange rate before FOMC decisions[88]).

"The key hidden parameter that defines informational herding theory is the private information held by traders."
—Park and Sgroi, 2016

Expert judgment

As a rule, expert judgment is a powerful complement rather than an alternative to statistical methods. Experts can provide valuable insights and contextual understanding that may not be captured by statistical models alone. Here are a few ways in which expert judgment complements statistical methods:

– Formulating economic theory behind a macro strategy can provide a solid foundation and rationale for the trading approach. While it may not always be necessary to create a successful strategy, looking for inspiration in economic theory can be good practice for several reasons, such as a deeper understanding of the fundamental drivers, identifying key relationships, awareness of changing circumstances capable of breaking up vital relationships to allowing traders to stay ahead of market trends and make proactive trading decisions. Understanding of economic theory allows traders to build on academic research: by drawing inspiration from established economic theories, traders can benefit from the wealth of knowledge and insights generated by economists and researchers in the field.
– Interpreting data: Experts have domain knowledge and expertise in the subject matter, allowing them to interpret the meaning of data accurately. They can provide context and explain the nuances of the data. For example, some business surveys that refer to a particular month actually use data collected in the previous month.
– Assessing data relevance: the experts can identify which data elements are most meaningful and informative for the analysis. For example, in some countries, core inflation (excluding food and energy) is a very important benchmark for policy rates, while in other countries, the central bank would only look at headline inflation.
– Detecting data distortions: Experts can recognize data distortions caused by factors such as changes in tax policies, regulated prices, natural disasters, or calendar effects. By considering these distortions, experts can provide adjustments or insights to ensure a more accurate analysis.
– Incorporating qualitative information: Statistical methods typically focus on quantitative data, but experts can provide qualitative information and insights that enhance the analysis. This qualitative knowledge may include information about market conditions, industry dynamics, policy changes, or geopolitical events that can influence the interpretation of statistical results.
– Validating statistical findings: Experts can validate and verify statistical findings by applying their knowledge and experience to assess the plausibility and reasonableness of the results. They can identify potential limitations or alternative explanations that statistical methods alone may overlook.

5.2 Detecting implicit subsidies

Implicit subsidies in financial markets are premia paid through transactions that have motives other than conventional risk-return optimization. They manifest as expected returns over and above the risk-free rate and conventional risk premia. They arise from large transactions or related announcements that are not motivated by conventional portfolio optimization, such as government policy objectives, convenience yields of holding certain assets, non-standard risk aversion, and behavioral biases, such as salience bias and loss aversion. Implicit subsidies are a bit like fees for services that are opaque rather than openly declared. Hence, detecting and receiving implicit subsidies is information-intensive but creates stable risk-adjusted value. Implicit subsidies are receivable in all major markets, albeit at the peril of crowded positioning and recurrent setbacks. It is critical to distinguish strategies based on implicit subsidies, which actually create investor value through information efficiency, and those that simply receive non-directional risk premia, which are based on rough proxies and do not create risk-adjusted value.

Understanding implicit subsides

From risk premium to implicit subsidy

Implicit subsidy here is defined as the expected return of a financial contract over and above the risk-free equilibrium rate and its conventional risk premium in an efficient market. The conventional risk premium arises from the uncertainty of payoffs and the correlation structure of contracts in conjunction with agents' aversion toward risks. Roughly speaking, a risk premium is the average expected compensation for bearing uncertainty. Standard asset pricing theory argues that in equilibrium the risk premium paid for holding a capital asset is commensurate to its price sensitivity to overall market value multiplied by the market risk premium. This means that the individual asset's risk premium increases with its volatility and market correlation. The market risk premium in these standard models depends on the probability distribution of a market portfolio and the risk aversion of a 'representative investor'.

The implicit subsidy comes about through violations of conventional market efficiency. The term implicit subsidy is not widely used in financial market theory and is chosen here to clearly distinguish it from conventional compensation for risk. It is important for the construction of trading strategies. Detecting and receiving implicit subsidies leads to positive expected risk-adjusted returns by conventional metrics. In general, an implicit subsidy can be viewed as a payment for service, typically in the form of positioning in accordance with other private agents' personal and economic interests or governments' political interests.

"Quantifying the implicit subsidy to banks has generated considerable interest over recent years. The numbers are striking, both in their sheer scale, but also in their variation."
—Bank of England, 2012

The sources of implicit subsidies

Generally, implicit subsidies result from large-scale transactions or related announcements that are not motivated by conventional optimization of portfolio risk and return. Market flows have the power to drive a wedge between transaction prices and contract value because they consume liquidity and change the market risk assessment of other investors and market makers (view The price effects of order flow[89]). Implicit subsidies can be persistent in the presence of large and repeated flows or standing intervention commitments. Indeed, there are many examples of these:

– A common source of implicit subsidies is interventions or intervention commitments of governments and central banks for the purpose of macroeconomic policy objectives. The prime example is foreign exchange interventions in conjunction with the imposition of positive real interest rate differentials relative to funding currencies. This policy is often used to tackle supposed exchange rate misalignment and to support local price and financial stability (view Why and when central banks intervene in FX markets[90]). It represents an implicit subsidy because international investors receive elevated real rates on local deposits, better liquidity in FX spot and forward markets, and reduced return volatility due to central banks' "leaning against the wind". Many economists also suggest that central banks have generally subsidized developed equity, bonds, and credit markets over the past two decades by setting highly accommodative refinancing conditions and systematic direct intervention in asset markets, particularly in times of financial distress (central bank 'put'). This subsidy has benefited particularly the 'risk parity

long-long trade', balanced risk exposure to both bond and equity markets, one of the most successful simple trading strategies in the 2000s and 2010s (view The mighty "long-long" trade[91]).

– Another common implicit macro subsidy is convenience yields, defined as premia for holding the underlying physical product or asset of a derivative. Examples of convenience yields include premia paid by industrial users in certain commodity spot markets for the availability of physical inventory (view Commodity pricing[92]) and premia paid by financial institutions for holding low-risk government bonds that can be used as collateral in securitized transactions and that incur low regulatory capital charges (view Multiple risk-free interest rates[93]). Interestingly, it is not only the convenience itself that may indicate an implicit subsidy but also the risk around it. In the commodity space, convenience yield risk estimates have positively predicted future commodity future returns (view Convenience yield risk premia[94]).

– Some agents pay up for reputation and the benefit of ongoing involvement in the market. For example, issuers of securities with low ratings and volumes, such as EM local currency bonds, are often willing to pay extra for market access. Specifically, they typically need to pay a premium to investors for low average market liquidity and high liquidity risk (i.e. the risk of trading costs rising when the need to trade increases) (view Basics of market liquidity risk[95]).

– Even financial investors pay implicit subsidies if they are highly averse to non-standard types of risk. Very few market participants optimize return-risk ratios purely according to textbook models. The price of risk can be heavily influenced by cognitive biases and institutional rules. For example, a widely documented behavioral bias is that agents exaggerate the probability of extreme events if they are acutely aware of them. This has been labeled "salience theory" (view How salience theory explains the mispricing of risk[96]) and implies that many market participants pay over the odds to avoid risk that is clear and present and skewed to the downside. Another behavioral bias that induces implicit subsidies is "fear of drawdown", i.e. aversion to large protracted losses. According to experimental research, this fear is more prevalent in risk perceptions than dislike of volatility. Also, institutional investors have reason to avoid showing outright losses at the end of reporting periods, and professional traders are constrained by so-called "drawdown limits". As a result, both will pay over the odds to shed or protect positions that might lead them past these barriers. Conversely, investors who are willing to endure protracted drawdowns that are due to biased positioning are paid subsidies, maybe in the form of fire sale prices, and can reap disproportionately higher volatility-adjusted returns in the long run (view Fear of drawdown[97]). This sometimes benefits specialized "distressed funds". Indeed, variance swap data suggest that investors pay elevated premia to hedge against price variance after a market price drops (view What variance swaps tell us about risk premia[98]). Also, financial regulation and accounting rules can encourage institutional investors to pay subsidies. For example, increased capital requirements for mark-to-market risk on the balance sheets of banks and insurance companies after the great financial crisis have apparently contributed to rising risk spreads (view The rise in risk spreads[99]), i.e. a widening gap between expected returns of assets with volatile prices and so-called risk-free short-term fixed income assets.

– Behavioral theory and experimental evidence suggest that irrational decision-making along the lines of "prospect theory" gives a more realistic description of investor actions than standard utility maximization. Indeed, "prospect theory value", based on the past return distribution of an asset, is a valid investment factor, particularly when market efficiency is compromised (view Prospect theory value as investment factor[100]). For example, private investors are more sensitive to losses than to gains, a phenomenon called "loss aversion" (view How loss aversion increases market volatility and predicts returns[101]). Loss aversion manifests, for example, in the risk reversal premium, i.e. overpricing of out-of-the-money put options relative to equivalent out-of-the-money call options (view The risk-reversal premium[102]). Loss aversion also implies that risk aversion is changing with market prices. This means that the compensation an investor requires for holding a risky asset varies over time. Changing attitudes towards risk translate into changing equity premia and there is evidence that this makes equity return trends predictable (view Predicting equity returns[103]). From the perspective of investors with low or stable risk aversion, such premia can be estimated and received when sufficiently high. There is a broad range of market risk perception measures available for this purpose (view The 1×1 of risk perception measures[104]).

– Many institutions also overcharge for volatility risk for reputational reasons. Thus, foreign investors in small and emerging bond markets will often charge a premium on local yields in accordance with exchange rate risk and volatility simply because they account in USD and have only limited hedging capacity. In times of unusually high FX volatility, this translates into elevated premia (subsidies) for local rates receiver positions (view FX risk and local EM bond yields[105]). More generally, EM bond markets seem to contain active fund risk premia. The active fund risk premium of a security would be the product of its beta premium sensitivity and price for exposure to active fund risk (view Active fund risk premia in emerging markets[106]). Both components change over time and mutually reinforce each other in episodes of negative fund returns and asset outflows. This explains why securities with high exposure to active fund risk command high expected returns. From the perspective of an investor with stable risk aversion, the highest subsidies would be receivable in bonds that are popular longs or overweights and in times of capital outflows.

The risks of trading implicit subsidies

In equilibrium, a subsidy prevails for as long as the market impact of subsidy payers exceeds the market impact of subsidy receivers. If trades and factors related to a subsidy become very popular, the original subsidy is being eroded. Instead, investors simply receive a conventional risk premium when engaging in a crowded trade. This is a premium for non-directional systematic risk and a source of "fake alpha" (view Fake alpha[107]). What is worse, even the conventional risk premium can be compressed to or below zero by so-called alternative risk strategies. Unlike implicit subsidies, non-directional risk premia require almost no research and are not a reliable source of value generation. They are just payments for under-appreciated risk and embellish conventional portfolio performance statistics.

Indeed, a common drawback of subsidies is that they attract crowds and, like all crowded trades, incur the risk of sudden outsized drawdowns when conditions change. This is a form of "setback risk" or endogenous market risk (view Section 5.4: Endogenous market risk in this handbook for more details). Setback risk is changeable. It is usually low before a subsidy is widely recognized or after "shake-outs". It is usually high when a subsidy-induced trade is touted by brokers or even popular media. Hence, setback risk does not generally invalidate subsidies. However, its consideration is complementary to strategies based on implicit subsidies.

Strategies that reap implicit subsidies are sometimes correlated with carry strategies. But they are not generally equivalent. Carry is simply the return an investor receives if market prices are unchanged (view Cross-asset carry: an introduction[108]). Carry is typically cheap in terms of data requirements and easy to calculate. That is why it is popular. It is also true that carry often increases with subsidies and risk premia. However, it is at best a very crude measure for implicit subsidies, lacking in precision and robustness. In the worst case, carry can become negatively related to implicit subsidies if crowds of investors use it for positioning without considering the actual risk-return trade-off. In this case, carry investors end up paying implicit subsidies to the rest of the market.

"While there may well be more diversity in the types of strategies hedge funds follow, there is also considerable clustering, which raises the prospect of larger moves in some markets if conditions lead to a general withdrawal from these 'crowded' trades." —Timothy Geithner, 2004

Popular strategies based on implicit subsidies

Foreign exchange

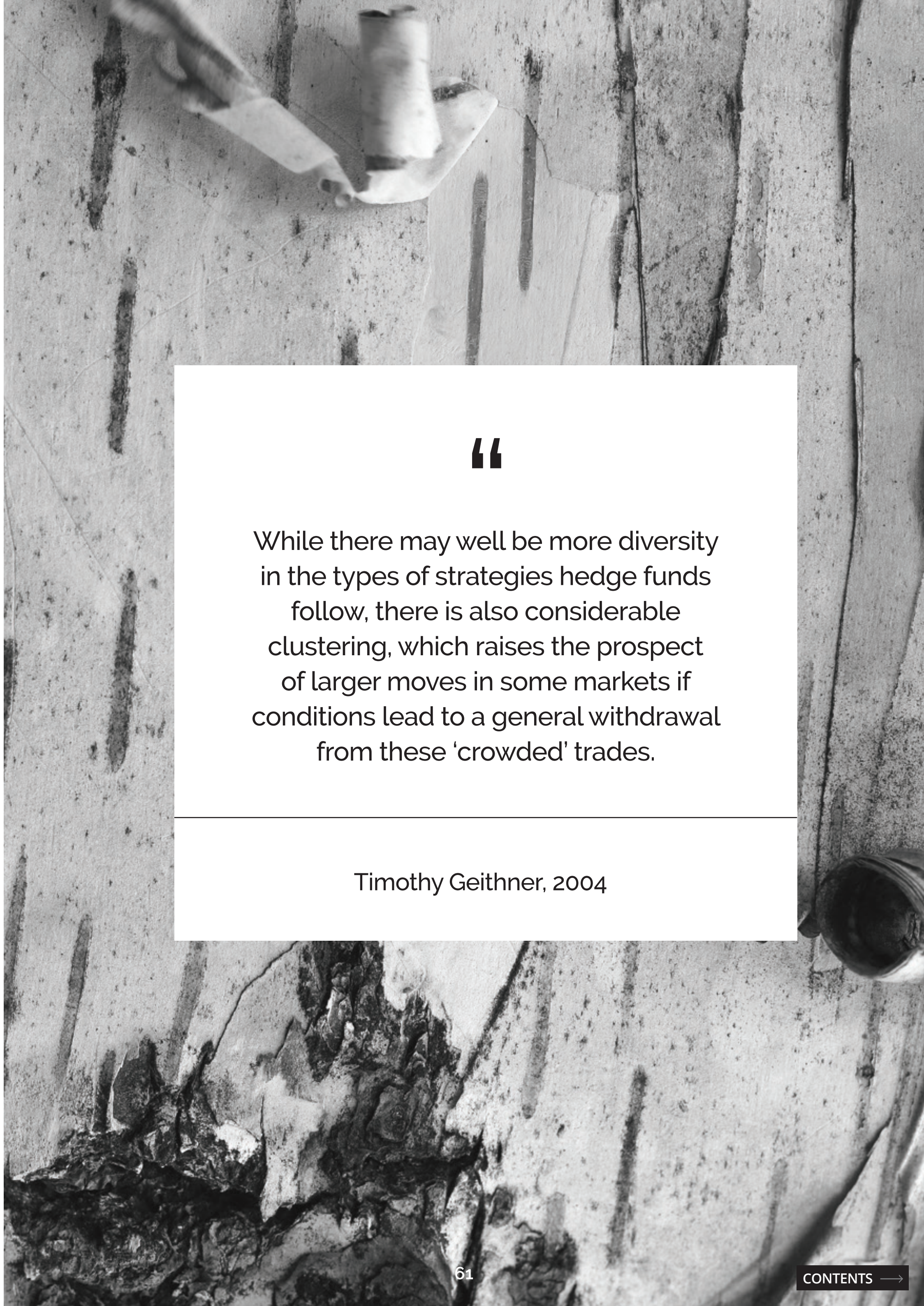
The FX carry trade (view How to use FX carry in trading strategies[109]) is probably the most popular strategy that has benefited from implicit subsidies. On its own, it is not a reliable estimate of expected returns. However, at times (particularly in the 2000s) positions in floating and convertible currencies with significant real carry reaped two types of implicit subsidies.

– Government support: central banks often set high real local short-term interest rates and engage in FX interventions to reduce inflation and attract capital flows. Such policies improve the risk-return trade-off of agents that lend locally and fund in foreign currency. Empirical research shows that official currency interventions can cause persistent external imbalances and over- or under-valuation of currencies (view Official flows and consequences for FX markets[110]) as a consequence of the portfolio balance effect. Moreover, central banks that lean against the wind of carry flows through sterilized currency interventions create an FX forward bias, i.e. a state where expected currency changes compound interest differentials rather than offset them (view Explaining FX forward bias[111]).

CONTENTS ⟶

Suppressed valuation and forward bias imply subsidies to the market.
– Private insurance premia: when local currency depreciation is a clear and present concern, corporates, banks, and households often prefer holding funding currencies to protect their business and mere subsistence. For example, financial institutions hold precautionary positions in U.S. dollar assets as protection against funding pressure (view How banks' dollar holdings drive exchange rate dynamics[112]). This gives rise to a safety premium on the dollar. Also, in EM economies, companies often buy dollars during crisis periods to secure liquidity for international transactions. Accepting negative expected returns in such situations is like paying insurance premia. Indeed, FX carry trades have historically been most profitable when fear of disaster triggered both high interest rates and undervaluation (view Disaster risk and currency returns[113]). Likewise, there is evidence that high-risk aversion, as measured by volatility risk premia, differences between options-implied and actual volatility, leads to undershooting and subsequent outperformance of carry currencies (view Volatility risk premia and FX returns[114]).

FX carry opportunities depend on market structure and regulation. In emerging markets, observed carry typically contains a combination of classic interest rate differential and an arbitrage premium that reflects the structure, regulation, and pressure points of on-shore and off-shore markets (view The nature and risks of EM FX carry trades[115]). This arbitrage premium is also called cross-currency basis. For example, a negative dollar cross-currency basis means that the FX forward implied carry of a currency against the USD is larger than the corresponding on-shore short-term interest rate differential. After the global financial crisis, 2008-09, periods of sizable dollar cross-currency basis have also been observed in developed markets. They reflect arbitrage frictions due typically to a combination of regulatory restrictions and short-term funding pressure (view Understanding dollar cross-currency basis[116]). In most cases, a negative dollar funding basis increases the implicit subsidy paid by the FX forward market. If synthetic funding rates are higher than on-short interest rate differentials there is a shortfall of the funding currency in offshore markets and an implicit subsidy of those willing to lend via FX swaps (view Understanding dollar shortages and related market dynamics[117]), i.e., selling spot and buying forwards, FX carry trades also illustrate the inherent vulnerability of subsidy-based investment strategies. Positive carry typically encourages capital inflows into small and emerging markets. This helps to compress inflation but is also conducive to a domestic asset market boom. Because of the former, the central bank does not fight the latter. In this way, FX carry strategies can produce self-validating flows. Financial markets create their own momentum. Conversely, a reversal of such flows is self-destructing (view Self-fulfilling and self-destructing FX carry trades[118]). To bring trading signals closer to actual subsidies, much can be done to enhance simple carry metrics (view How to use FX carry in trading strategies[119]). The most plausible additions are adjustments for inflation differentials, consideration of market correlation premia, penalties for poor



"

While there may well be more diversity in the types of strategies hedge funds follow, there is also considerable clustering, which raises the prospect of larger moves in some markets if conditions lead to a general withdrawal from these 'crowded' trades.

Timothy Geithner, 2004

economic performance (view Modified and balanced FX carry[120]), and external deficits. Also, adjustments for estimated currency over- or undervaluation are conceptually compelling (view Advanced FX carry strategies with valuation adjustment[121]). Enhanced carry strategies have historically produced much more consistent investor value.

Carry is the most popular but not the only indicator related to implicit subsidies in FX markets. Another approach is estimating the hedge value of currencies. Depending on the circumstances, some currencies tend to strengthen against the USD when global or U.S. equity prices fall. An expected negative correlation with the market portfolio means that investors pay a premium for holding such a currency in a diversified portfolio. This preference translates into an implicit subsidy for those willing to short it on its own. Analogously, the expected positive correlation of a currency with broader market benchmarks means that investors require a discount for holding that currency in a diversified portfolio. This translates into a subsidy for those willing to be long the currency. The hedge value of a currency, as priced by the market, can be inferred directly from "quanto index contracts" (view FX strategies based on quanto contract information[122]). "Quantos" are derivatives that settle in currencies different from the denomination of the underlying contract.

> "Suppose that a country is temporarily risky: it has high interest rates, and its exchange rate is depreciated. As its riskiness reverts to the mean, its exchange rate appreciates."
> —Farhi and Gabaix, 2004

Fixed income

Implicit subsidies in government bond markets and interest rate swap markets often arise from two sources:

– Funding conditions: Central banks steer refinancing conditions in accordance with inflation targets and financial stability objectives. With the rise of non-conventional monetary policy, central banks have become able to exert influence through a wide array of instruments, including short-term refinancing rates, longer-dated repurchase agreements, asset purchase programs, and collateral policies.
– Convenience yields: Fixed-income securities are commonly used for purposes other than risk-return optimization. Common examples include liability hedging (for pension funds and insurance companies) and collateralization of secured transactions. The latter would imply that some high-grade bonds have value beyond return. U.S. government bonds, in particular, seem to provide a sizable, consistent convenience yield that tends to soar in crises (view Multiple risk-free interest rates[123]).

Implicit subsidies in fixed-income markets typically affect real yields (for cash investors) and real carry (for leveraged investors). Real bond yields rise and fall with risk premia and subsidies. They need to be estimated based on some model of inflation expectations. Simple estimates have proven powerful predictors of government bond returns (view The predictive power of real government bond yields[124]).

Fixed income carry is a combination of yield spread and curve rolldown. For example, accommodative refinancing conditions in conjunction with inflation

concerns lead to steep yield curves, i.e. high carry, at the time when a subsidy is paid. However, as for foreign exchange, fixed income carry is a very rough and imprecise indicator for subsidies. At the very least it must be adjusted for rational short rates expectations, for example by considering the gap between current short-term real rates and their plausible medium-term equilibrium level (view Fixed income carry as trading signal[125]).

Risk premia and subsidies for inflation risk have historically been paid by the obligor to the creditor because the dominant issuer of fixed-income securities in most countries has been the public sector, which does not optimize financial risk-return relations. This includes inflation risk premia since governments are insensitive to inflation, while the dominant end investors are private households, which are averse to inflation. Inflation risk premia can vary across time. For example, they were compressed in the era of non-conventional monetary policy (view The fall of inflation compensation[126]).

A useful indicator for risk premia in fixed-income markets is the duration volatility risk premium, the scaled difference between swaption-implied and realized volatility of swap rates' changes. Two derived concepts of volatility risk premia hold particular promise for measuring implicit subsidies (view Duration volatility risk premia[127]). Term spreads are the differences between volatility risk premia for longer-maturity and shorter-maturity IRS contracts and are related to the credibility of a monetary policy regime. Maturity spreads are the differences between volatility risk premia of longer- and shorter-maturity options and should be indicative of a fear of risk escalation.

> "Due to the risk of changes in inflation, inflation compensation generally contains an inflation risk premium."
> —International Journal of Central Banking, 2015

Credit

Generally, obligors with significant credit risk must compensate investors for the implicit option to default. This is not in itself a subsidy but just an option premium. However, obligors sometimes pay premia higher than justified by their actual default probability for the convenience of having stable market access and to compensate investors for research and information costs.

Moreover, smaller and lower-rated obligors typically have to pay a significant "illiquidity risk premium". This premium compensates investors for tying up their capital for some time and for forfeiting the option of containing losses and adapting positions to changing circumstances. Importantly, there is evidence that this illiquidity risk premium is time-variant and particularly high during and pursuant to periods of market distress (view The illiquidity risk premium[128]). Hence, taking credit risk in distress times by distinguishing between actual default risk and excess illiquidity risk premia is a valid strategy for reaping implicit subsidies.

Commodity futures

Implicit subsidies are also paid in commodity futures. The futures curve reflects storage and funding costs, supply and demand imbalances, convenience yield, and hedging pressure. Convenience and hedging can give rise to an implicit subsidy, i.e., a non-standard risk premium, and make commodity carry a valid basis for a trading signal (view Commodity carry as a trading signal – part 1[129]).

Unlike other financial derivatives, storage constraints of the underlying materials obstruct the arbitrage of commodity futures across maturities. The costlier the storage, the greater the barriers and the more volatile the implied carry (view Commodity carry[130]). To detect implicit subsidies, futures curves of commodities with high storage costs should be adjusted for predictable supply and demand swings across time, such as seasonal factors (view Seasonal effects in commodity futures curves[131]) and temporary gluts or shortages in the underlying. Properly adjusted, a relatively low futures price ("backwardation") typically indicates a subsidy being paid to the longs in the future. A relatively high futures price ("contango") may indicate a subsidy being paid to the shorts in the future. There are several sources of such subsidies:

– Often, industrial users of commodities pay "convenience yields" for materials they like to have in store. This is a cause of backwardation and can be interpreted as implied "leasing rates" for physical commodity on-premise. Holding physical inventories increases supply security and flexibility for production and thus provides benefits over and above financial return. The value of such inventories increases with their scarcity. Convenience yields are the basis of a rational asset pricing model for commodities (view Commodity pricing[132]) and help to predict future demand and price changes (view Understanding convenience yields[133]). Importantly, the effective premium paid through the convenience yield depends on risk factors in other asset markets (view Commodity trading strategies and convenience yields[134]). Due to the "financialization" of commodities, there will often be a link between investors' willingness to hold convenience claims and their risk exposure in bond, equity, and other financial markets. It is harder to find convenience providers in times of financial distress.

– Both producers and consumers of commodities are often willing to pay a premium for hedging future demand or supply, a tendency that was formulated in the "hedging pressure theory" (view Risk premia in energy futures markets[135]). For example, in markets where the balance of hedging is on the producer side, future supply may be sold with a discount, by itself leading to a backwardation and positive carry (view Commodity futures curves and risk premia[136]).

– There is also evidence that some commodity futures pay variance risk premia, i.e. high option implied volatilities relative to expected actual return volatility, in times of high uncertainty for investors (view Volatility risk premia in the commodity space[137]). This premium can be thought of as the compensation demanded by financial investors for changes in volatility. Financial investors with strict risk management procedures tend to overpay for such protection. Their role in commodity markets has increased markedly since the 2000s.

"Convenience yield can be thought of as the interest rate paid in barrels of oil for borrowing one barrel of oil."
—Bank of Canada, Working Paper, 2014

Equity

Financial market participants are always net owners of shares in companies. Exposure to equity is undiversifiable risk. The basis for risk premia and implied subsidies is uncertainty about earnings and the discount factor that is applied to them. This uncertainty manifests in high price volatility in share price compared to high-grade fixed-income markets. Moreover, initial capital owners often pay a subsidy to receive financing and share risk. Altogether, since 1900 equity investors have been paid a significant premium for bearing equity price risk: according to a long-term global study, real equity returns have been 5% per annum, versus just 1.8% for government bonds and 1% on short-term deposits (view Lessons from long-term global equity performance[138]).

The equity premium depends on both the actual riskiness of payoffs (determining the quantity of risk) and risk aversion (determining the price of risk). If there were only homogeneous and rational risk aversion, the equilibrium premium in equity markets would not be a subsidy. However, it is common for parts of the market to develop unusually high or low risk aversion. For example, fear of drawdown rises when portfolio managers are close to loss limits or at the end of an investment period. This fear can give rise to implicit subsidies paid to investors with stable risk aversion.

– Estimates of this subsidy can be based on the variance risk premium (or volatility risk premium), a premium paid to those bearing the risk of volatility of volatility. The variance risk premium is often measured by the difference between options-implied and expected realized variance (view Understanding and dissecting the variance risk premium[139]) or the difference between variance swap rates and expected realized variance (view Variance term premia[140]).

– Analogously, subsidies may be estimated based on the premium charged for the uncertainty of the correlation of securities among each other or with a market benchmark. This is called correlation risk premium and arises from the common experience that correlation surges and diversification decreases in market crises, summarized in the adage that in a crash "all correlations go to one" (view The correlation risk premium[141]). Correlation risk premia can be estimated based on option prices and their implied correlation across stocks.

In normal or quieter times, investors often overpay for stocks with higher volatility and market beta (view The low-risk effect: evidence and reason[142]). This is because many are constrained in their use of financial leverage and high-volatility stocks giving them greater market exposure and higher expected absolute returns. As a consequence, risk-adjusted returns of high-volatility stocks have historically underperformed those of low-volatility stocks, a phenomenon that is called the "low-risk effect" and that can be exploited by leveraged investors in the form of "betting against volatility" or "betting against beta" (view The "low-risk effect" in financial markets[143]). There is a whole range of stylized low-risk strategies discussed in financial research that seems to have produced consistently alpha over time (view The basics of low-risk strategies[144]).

Similarly, investors seem to overpay for stocks that have high "emotion betas", i.e. the emotional "glitter" of stocks, measured as sensitivity to the emotional state of the market (view The emotion beta of stocks[145]). Empirical research suggests that emotion betas significantly and positively predict subsequent return differentials across stocks. This is backed by theories of emotional utility in investments that imply the predictable behavior of investors who covet emotions. Equity also seems to pay a statistical arbitrage risk premium (view Statistical arbitrage risk premium[146]). Assets can be hedged against factor exposure through peer assets. The expected return on a hedged position is the arbitrage risk premium, which is estimable, for example, by 'elastic net' machine learning. 'Unique' stocks have higher excess returns than 'ubiquitous' stocks. This is a valid basis for trading strategies.

"The equity risk premium is the extra return that investors demand over and above a risk free rate to invest in equities as a class. Thus, it is a receptacle for investor hopes and fears, with the number rising when the fear quotient dominates the hope quotient." —Aswath Damodaran, 2013

Volatility markets

Option-implied volatilities price implicit subsidies if the market is compromised by "moral hazard". The direction of the subsidy typically depends on the state of the market.

– Portfolio managers that receive annual performance fees have an incentive to "sell tail risk", which will enhance their conventional risk-adjusted returns. On the rare occasion that such tail risk materializes, the resulting losses will not symmetrically reduce the manager's income. More importantly, investment companies often maximize assets under management, and their investors allocate to funds with better recent performance. This creates a bias for portfolios with steady above-par payouts (or steady above-par expected mark-to-market gains) in exchange for elevated explicit or implicit tail risks (view How growing assets-under-management can compromise investment strategies[147]). The bias tends to be strongest in "good times" when competition for fund inflows is high. It leads to discounted insurance premia for option-implied financial risk that can be measured and gainfully used for long-volatility and tail risk strategies.
– In turbulent times, institutional investors have the incentive to pay excessive premia to contain volatility risk, as assets, jobs, and the reputation of managers are threatened by violations of risk limits and maximum drawdown limits.

The price information of volatility markets helps identify subsidies in underlying assets. Generally, volatility markets are indicative of the price charged by financial markets for exposure to both known and unknown risks (view Volatility markets: a practitioner's view[148]). As mentioned above, the willingness of market participants to pay up to protect against volatility can be measured by the variance risk premium, the difference between options- or swap-implied volatility, and expected realized return volatility.

– Historically, the variance risk premium has been positive in the long run and fairly consistently so (view Variance risk premia for patient investors[149]). It compensates investors for taking short volatility risk. A short volatility position typically produces a positive correlation with the equity market and occasional outsized drawdowns.
– For short-term trading strategies, the variance risk premium can be estimated in a timely and realistic manner by choosing an appropriate lookback horizon and considering the mean-reverting tendency of volatility (view Realistic volatility risk premia[150]). The premium paid for such volatility insurance has been a predictor of FX returns (view Volatility insurance and exchange rate predictability[151]), equity returns, gold futures returns (view Gold: risk premium and expected return[152]), and option strategy returns (view The importance of volatility of volatility[153] and Variance term premia[154]). The directional bias of variance risk premia can be gauged through measures of downside variance premia, the difference between options-implied and actual expected downside variation of returns, and skewness risk premia, the difference between upside and downside variance risk premia (view The downside variance risk premium[155]). Over and above the standard variance risk premium, markets also seem to be paying a "volatility of variance premium". While the former relates to uncertainty about volatility, the latter relates to uncertainty about the volatility of volatility, a conceptually and empirically different factor (view The importance of volatility of volatility[156]).

"Volatility trading is about putting a price on known unknowns and unknown unknowns." —Christopher Cole, 2014

Risk-parity

Risk-parity means equal exposure to different investment positions in terms of risk metrics, such as expected return volatility. One of the most successful investment strategies in the 2000s and 2010s has been the risk-parity "long-long" of combined equity, credit and duration derivatives. In simple terms, this trade takes continuous joint equal mark-to-market exposure in equity or credit and duration risk. There have been three apparent contributors to this success: undiversifiable risk premia, implicit subsidies paid by central banks, and great diversification benefits from negative return correlations (view The mighty "long-long" trade[157]).

The macro environment is changeable, however, and a strong theoretical case can be made for managing risk parity strategy based on economic trends and risk-adjusted carry that indicate and predict implicit subsidies. For example, overheating scores, which indicate the withdrawal or enhancement of central bank support, have been strongly correlated with risk parity performance (view Macro factors of the risk-parity trade[158]).

5.3 Estimating price distortions

Price distortions are apparent price-value gaps. Trading strategies that are based on such distortions rely less on information advantage than on consistent price monitoring, flexibility of trading, privileged market access, superior financial product knowledge and – most of all – rational discipline in turbulent times. Price distortions arise from inefficient flows and prevail as long as a sizable share of market participants is either unwilling or unable to

CONTENTS

respond to obvious dislocations. There are many causes of such inefficiencies, including risk management rules, liquidity disruptions, mechanical rebalancing rules and government interventions. This section is based on the blog Price Distortions[159].

The basics

What are price distortions?

In the present context price distortions are defined as deviations of quoted prices from a level that would clear the market if all participants were trading for conventional risk-return optimization. In principle, all flows distort transaction prices relative to contract value (view The price effects of order flow[160]). However, mostly the effects are small. Price distortion here means significant gaps between mark-to-market prices and a plausible range of economic values of a contract.

Like information inefficiency, price distortions lead to a mispricing of financial contracts relative to their fundamental value. Unlike information inefficiency, this mispricing is not based on ignorance, but on "inefficient flows". These are transactions in financial markets that are motivated by objectives other than return optimization. In practice, one can observe many market flows and transactions that obstruct the alignment of price and value. Common causes or triggers for such "inefficient flows" include:

– formal and rigid risk management rules that apply to many institutions,
– liquidity shocks, i.e. a sudden deterioration of the tradability of assets or the risk thereof,
– mechanical allocation rules, for example of exchange-traded funds, indexed fund and related structured products, and
– government intervention and regulation.

"Financial markets are open, adaptive, out-of-equilibrium systems that are subject to nonlinear dynamics, created particularly but not only by imitation and herd behavior." —Sornette and Cauwels, 2014

"The tendency for experimental markets for long-lived assets to price at levels that differ from intrinsic values is one of the most robust and puzzling results from research in experimental markets." —Breaban and Noussair, 2015

Detecting price distortions

Unlike information-based trading, price distortion-based strategies do not require information advantage in respect to the traded contract. They do not focus on in-depth research of its expected value. Instead, these strategies ascertain some apparent price-value gap and market inefficiency. They subsequently use advantages in market access or in pricing know-how to extract value. Sometimes, trading speed (view High-speed trading: lessons from quantum physics[161]) and financial leverage can be of the essence. Detecting inefficient flows and related distortions is not trivial. Most of what is commonly called "market noise" is actually rational trading disguised by complexity (view Market noise[162]). However, price distortions frequently do arise pursuant to major information or price shocks that create a state of confusion or even panic. Moreover, trading in times of turmoil often bears high transaction cost, which deters market participants from immediately taking advantage of price-value gaps. In order to detect price distortions systematically one can take three different angles:

– The first is to understand and identify the causes of distortions, such as institutional risk management constraints, market liquidity problems and so forth, which are explained in the sections below. If a market is being heavily influenced by any of these causes, it is more probable that prices will be regularly distorted and that there will be payback. For example, empirical evidence suggests that a wide range of equity return anomalies is related to market inefficiencies (view Equity return anomalies and their causes[163]). Malfunctioning markets can be diagnosed in real-time with the help of "market distress indices" that include issuance volumes and issuer characteristics in the primary market and trading volumes and liquidity in the secondary market (view Building a real-time market distress index[164]).
– The second angle is metrics of misalignment between prices and fundamental value, such as in financial bubbles (view Identifying asset price bubbles[165]). Diagnosing price distortions this way is not the same as estimating price-value gaps, as the latter would require superior information efficiency. Price distortions can be detected by conventional valuation metrics but with a focus on extreme price value gaps that are associated with obstacles to arbitrage or trading. An example would be gaps between the credit spreads of individual bonds and a plausible grid of credit spread curves that is estimated based on a range of maturities and ratings.
– The third approach is to investigate the time-series pattern of asset prices. For example, higher than-exponential asset price growth with apparent feedback loops is often an indication of an unsustainable asset price bubble (view How to recognize an asset price bubble[166]). Also, temporary mild explosiveness in asset prices or exchange rates in conjunction with relative stability in underlying fundamentals is usually indicative of short-term distortions (view Explosive dynamics in exchange rates[167]). Generally, a self-reinforcing price dynamics that is not a reflection or cause of underlying value changes is prone to producing price distortions. Technically, price distortion time series are characterized by "strict local martingales", i.e. episodes when the risk-neutral return temporarily follows a random walk while medium-term return expectations decline with the forward horizon length. Such strict local martingales can be identified by modeling return volatility with the help of a recurrent neural network (view Detecting market price distortions with neural networks[168]).

Price distortions prevail because most investors are either unable or unwilling to exploit them. This is very realistic.

– The vast majority of investors are unable to exploit relative price distortions because their access to arbitrage capital and leverage is restricted. These restrictions can hamper even sophisticated investors, particularly in times of financial turmoil. They are the very cause of persistent relative value opportunities, particularly in the fixed income space (view Fixed income relative value[169]).
– Meanwhile, many investment strategies explicitly disregard price distortions, and their flows may, for some time, overpower more subtle relative value flows. Simple trend following has been a common and successful algorithmic investment strategy (view Trend following in U.S. equities[170]) that deliberately blanks out the fundamental value of a contract

CONTENTS

altogether. Similarly, many discretionary traders follow "momentum strategies" based on perceived dominant information flows (trading on the news). Moreover, herding is a well documented behavioral pattern in the investment industry (view Herding in financial markets[171]) that can be efficient from the individual portfolio manager's perspective, because it saves research costs (view Why and when financial markets are herding[172]). Herding can, however, lead to price distortions, particularly if it is motivated by non-fundamental shocks in markets with limited liquidity and a homogeneous investor community, such as in corporate credit markets (view Credit market herding and price distortions[173]). Moreover, there is also reason and evidence of so-called "beta herding", which means convergence of market betas of individual assets that arises from investors' biased perceptions, such as overconfidence in predicting directional market moves (view Beta herding[174]). If assets have the 'wrong' beta, subsequent market moves will lead to price bias relative to underlying value and trading opportunities.

"Asset prices in some markets have persistently deviated from levels that would be consistent with the absence of arbitrage opportunities. Such distortions can occur when scarce funding or limited balance sheet capacity prevents investors from taking advantage of the resulting trading opportunities."—BIS Quarterly Review, September 2015

Price distortions and risk management rules

Risk (management) shocks

The risk management rules of most institutional investors follow commonly accepted standards. Alas, similar rules often coerce similar flows. And one-sided flows in markets with limited liquidity can push prices far from fundamental values. In this way, conventional risk management rules can be a cause of distortions and even set in motion self-reinforcing feedback loops.

Prominent risk metrics are value-at-risk (VaR), a statistical measure of expected maximum loss at a specific horizon within a specific range of probability, and expected shortfall, a measure of expected drawdown in a distress case. These statistical assessments of risk rely on historical variances and covariances and can be subject to sudden major revisions.

– The calculation of risk metrics depends on the lookback window, i.e. the history of the price return experiences used for its calculation and the weighting of recent versus distant observations. Lookback windows that rely on multi-year experience adapt poorly to a changing risk environment. Therefore, many risk metrics are short, with a half-time of lookbacks of no more than 11 days. This makes them susceptible to drastic reassessments based on market volatility alone. Such "statistical" reassessment would occur without any consideration of the underlying causes of changes in volatility.
– Even with many years of data history, risk estimates are still vulnerable to event shocks. Small variations in assumptions can cause large changes in forecasts.

"

Asset prices in some markets have persistently deviated from levels that would be consistent with the absence of arbitrage opportunities. Such distortions can occur when scarce funding or limited balance sheet capacity prevents investors from taking advantage of the resulting trading opportunities.

BIS Quarterly Review, September 2015

Some research claims that it would take half a century of daily price data for VaR and expected shortfall models to reach their theoretical asymptotic properties. Intuitively, even long historical samples have only limited data on actual crises and hence are subject to revision with each new crisis experience (view The risks in statistical risk measures[175]).

– Risk models are prone to compounding uncertainty when they matter most: in financial crises. Research shows that different types of statistical risk models tend to diverge during market turmoil and hence become themselves a source of fear and confusion (view How statistical risk models increase financial crisis risk[176]). Acceptable performance and convergence of risk models in normal times can lull the financial system into a false sense of reliability.

Reliance on statistical metrics can give rise to so-called 'VaR shocks': If estimated risk metrics surge, VaR-sensitive institutions recalibrate the risk of their existing positions and subsequently reduce their positions (view Quantitative easing and "VaR shocks"[177]). For example, if an institution has a fixed "statistical" risk budget, a doubling of the estimated value-at-risk or expected shortfall requires it to liquidate half of its nominal positions. Importantly, this type of selling pressure typically arises after the initial price decline.

Analogously, many trading desks or asset management companies set "drawdown limits" for their managers. These are loss thresholds for a portfolio's net asset value beyond which traders must liquidate part or all of their positions. Managers are typically under obligation to cut risk regardless of asset value and return prospects. Hence, once the common drawdown limits are broken additional flows ensue in the same direction of the original loss, accentuating price movements for no fundamental reason.

> "VaR is an untrustworthy measure of future market risk for one main reason: it is calculated by looking at the past."
> —Pablo Triana, 2010

> "We need half a century of daily data for the estimators to reach their asymptotic properties, with the uncertainty increasing rapidly with lower sample sizes."
> —DNB statistical paper on VaR and expected loss, 2016

Feedback loops

Initial shocks to risk metrics and related flows can team up with other forces to form feedback loops:

– **Dynamic hedging**: Many institutions run explicit or implicit "short volatility" positions. Indeed, such short-volatility strategies seem to have expanded strongly in the wake of declining fixed-income yields. They pay steady positive risk premia in normal times, just like a fixed-income asset, but at the peril of occasional outsized losses. Dynamic hedging refers to sales and purchases of underlying assets in order to contain the risk related to volatility. This gives rise to feedback loops in two ways.

- From a **macro perspective**, there is reinforcement between volatility and the scale of short volatility strategies (view The danger of volatility feedback loops[178]). In particular, there is a plausible feedback loop between low interest rates, debt expansion, (low) asset volatility, and financial engineering that allocates risk based on that volatility.
- From a **micro or trading perspective**, dynamic hedging is common practice for option books but is applied widely in other markets, including credit, rates and leveraged risk parity. For example, U.S. financial institutions have historically been "short volatility" with respect to long-term interest rates because of homeowners' option to repay mortgages early (view Overshooting of U.S. Treasury yields[179]). In times of declining yields, delta and probability of execution of this implied option increase, forcing institutions to hedge by further extending duration exposure. The probability of severe "convexity events" has been reduced since the Federal Reserve has bought a sizable share of mortgage-backed securities from the market (view How the Fed has reduced the risk of "convexity events"[180]), but not eliminated.

– **Credit risk:** Risk management can also form feedback loops with credit risk, particularly country risk and counter party risk. A good illustration of this is the Credit Default Swaps (CDS) market. CDS are assumed to represent a measure of default risk. In practice, this (less liquid) market can gap in large moves, simply as a consequence of one-sided institutional order flows, which themselves could be motivated by risk management or regulatory considerations (view Why CDS spreads can decouple from fundamentals[181]). As CDS spreads themselves are used as a measure of credit risk, institutional flows and spreads can reinforce each other to form escalatory dynamics.

– **Public fear:** Financial market turbulences typically focus popular attention on crisis risk. Bouts of fear of extreme events, such as economic depressions or war, are more frequent than the actual occurrence of disasters (view How fear of disaster affects financial markets[182]). In normal or good times, people tend to pay little attention to extremes. As economic or political conditions deteriorate, people begin to contemplate the possibility and consequences of disasters. Such enhanced awareness plausibly changes subjective expectations and the price of risk. This is called "salience theory" (view How salience theory explains the mispricing of risk[183]). If public fear of crisis is rising, financial risk managers experience pressure from investors, shareholders and even governments to position more defensively.

– **Redemptions:** Significant declines in the net asset values of investment vehicles usually give rise to redemptions, often from investors that cannot afford or bear watching wealth dwindling beyond certain thresholds. This is supported theoretically and empirically for equity, bond and credit markets (view Corporate bond market momentum: a model[184]). In many cases, funds provide daily liquidity and costs of redemptions are effectively borne by investors that do not redeem or redeem late. This creates incentives for fire sales and causes price distortions (view Mutual fund flows and fire sale risk[185]). Indeed, the pro-cyclicality of redemptions is consistent with survey evidence of pro-cyclicality of equity return expectations of investors (view How equity return expectations contribute to bubbles[186]).

CONTENTS

– **Forced deleveraging:** Risk-reduction in banks and other financial intermediaries does not only constrain their own asset holdings but, indirectly, those of other market participants, particularly leveraged investors such as hedge funds. This creates both relative price distortions and high directional risk premia. Most obviously, limitations of arbitrage capital give rise to price differentials between contracts with similar risk profiles (view Fixed income relative value[187]). Also, empirical analyses have found that the leverage provided by broker-dealers, i.e. their funding of others, is an important explanatory variable for the risk premium paid on equity and credit exposure (view Broker-Dealer leverage drives credit and equity prices[188]). When credit supply is ample, risk premia and future excess returns are low. When credit supply is scarce, risk premia and future excess returns are high.

> "Convexity hedging flows tend to exacerbate rate sell-offs, especially in the 5-10 year part of the curve, widen swap spreads and increase short-dated volatility." —Bank of America – Merrill Lynch Research, 2013

Price distortions and market liquidity

The various price effects of liquidity

Market liquidity here refers to the cost of buying and selling a security or derivative. It measures the efficiency of trading. Separately, market liquidity risk refers to the probability that trading costs surge when the need for trading becomes more urgent (view Basics of market liquidity risk[189]). Both liquidity and liquidity risk influence prices.

– First, most institutional and private investors are willing to pay a premium on securities with high and reliable liquidity and require a discount on securities with low and uncertain liquidity (view The illiquidity risk premium[190]). Illiquidity translates into higher transaction cost for a given trading pattern and eats into returns. The illiquidity risk premium is an excess return paid to investors for tying up capital. The premium compensates for the loss of flexibility to contain mark-to-market losses and to adjust positions to a changing environment.
– Second, changes in liquidity or liquidity risk of a contract lead to a change in its price, irrespective of its expected discounted present value. For example, a rise in market illiquidity, which means a greater cost of trading, makes forward-looking investors require higher future yields on a security. Thus, uncertain and unstable liquidity conditions lend themselves to price distortions. Small shocks can produce large price moves and apparent dislocations.

Poor liquidity can also cause rational price distortions when market participants keenly observe each other's positions and trading activity (view How poor liquidity creates rational price distortions[191]). For example, in OTC (over-the-counter or bilateral) markets, lack of liquidity means that dealers do not significantly "buffer" flows and institutional investors effectively transact with each other. In this case, investors take each other's bids and offers as signals and plausibly operate under the laws of game theory. In particular, when investors observe each other's selling pressure, they can rationally transact at prices below true value and give rise to so-called run equilibria, self-reinforcing price dynamics away from fundamental value.

There is evidence that liquidity as a price factor and source of price distortions has increased since the 2000s:

– Regulatory tightening after the great financial crisis has reportedly discouraged risk warehousing of banks, which would make global liquidity more precarious (view The growing concerns over market liquidity[192] and Bond market liquidity risks[193]). For example, in the U.S., the Volcker Rule has banned proprietary trading of banks with access to official backstops. Market making has become more onerous as restrictions and ambiguities of the rule make it harder for dealers to manage inventory and to absorb large volumes of client orders in times of distress (view Volcker Rule and liquidity risk[194]).
– By contrast, the role of institutional asset managers as liquidity providers has increased (view The rise and risks of euro area shadow banking[195]). Investment funds often buy and sell with the market, chasing return trends (view Trend chasing and overreaction in equity and bond markets[196]), due to redemptions and reliance on collateralized funding. Also, asset managers often engage in cash hoarding, which means that they sell more underlying assets in market downturns than is necessary to meet redemptions (view Cash hoarding and market dynamics[197]). This holds true, particularly in markets with more precarious liquidity. On the whole, investment funds seem to make liquidity more pro-cyclical and may aggravate market price swings, thereby giving rise to upside price distortions in bull markets and downside price distortions in downturns.

> "A rise in market illiquidity, which means a greater cost of trading, makes forward-looking investors require higher future yields on their investments for any given cash flows generated." —Yakov, Mendelson, and Pedersen, 2014

Past experiences

In the 2010s, there were many examples of price distortions and trading opportunities that were shaped by liquidity conditions.

– In developed foreign exchange markets, liquidity shocks have been highly cross-correlated. In systemic crises, FX liquidity shocks have formed negative feedback loops with funding constraints and volatility, leading to escalatory dynamics and fire sales (view Some stylized facts of FX liquidity[198]). Even regular episodes of tightening dollar funding conditions have triggered one-sided flows in FX swap markets. FX swap markets serve as a conduit for secured dollar funding. Large one-sided flows can lead to a breakdown in the conventional non-arbitrage condition of the "covered interest parity", leading to arbitrage or enhanced trading opportunities (view Covered interest parity: breakdowns and opportunities[199]). Such opportunities can be measured by the "cross-currency basis" and have become common since the great financial crisis (view Why the covered interest parity is breaking down[200]). Indeed, a new theory of risk-adjusted covered interest parity suggests that FX swap rates, i.e. the difference between FX spot and forward prices, deviate from risk-free interest rate differentials in accordance with the relative liquidity risk premia for the relevant currency areas (view The risk-adjusted covered interest parity[201]).

CONTENTS

– The 2013 sell-off in the U.S. treasury market ("taper tantrum") illustrated that dealers or intermediaries may reduce their own inventories and market making after risk shocks, thereby aggravating rather than buffering liquidity shocks (view Dealer balance sheets and market liquidity[202]). More generally, empirical research has shown that sudden large drawdowns in government bond markets are aggravated by poor liquidity (view The asymmetry of government bond returns[203]). This tendency could increase over time, as a consequence of increased capital charges on market making, extended transparency rules for dealers, elevated assets under management in bond funds and the liquidity transformation functions of these bond funds (view Liquidity risk in European bond markets[204]).

– Emerging markets appear to be particularly vulnerable to liquidity conditions. Assets under management of dedicated EM funds have increased markedly since the 1990s. Trading flows have been highly correlated due to the usage of benchmarks, and EM asset prices and final investor flows tend to be pro-cyclical and mutually reinforcing (view The pitfalls of emerging markets asset management[205]). The discretionary decisions of fund managers seem to aggravate this pro-cyclicality: they usually increase cash holdings in times of market turmoil due to increased risk of future client redemptions (view How EM bond funds exaggerate market volatility[206]). Local currency emerging debt markets, in particular, have become more vulnerable to global liquidity and other market shocks, with foreign ownership being a key determinant of that vulnerability (view On the vulnerability of local emerging debt markets[207]). As a consequence, global shocks can trigger sizable relative price distortions between markets and currencies that feature high foreign participation and those that are more isolated.

"Both retail and institutional investor flows to emerging market assets, and the total returns on these assets in US dollar terms, are generally pro-cyclical."
—BIS Quarterly Review, September 2014

Price distortions and rebalancing issues

What is rebalancing?

Rebalancing is the process of realigning the weights in a portfolio with the designed purpose of the investment vehicle or strategy. Rebalancing seeks to limit exposure to unwanted risk, regardless of whether that risk pays a high premium or not. The main rebalancing processes simply prescribe periodically buying or selling assets to maintain an original or desired allocation.

Rebalancing is a source of inefficient flows. Importantly, mechanical rebalancing rules are, in fact, active algorithmic strategies, even if they do not explicitly seek return optimization. For example, simple periodic reallocation to fixed asset weights means that winning assets are systematically sold and losers are bought. In markets with trends and relative price momentum, this creates losses and slows trends at the market level.

It is important to understand the motivation behind specific rebalancing flows in order to detect potential price distortions. Academic research shows that the effect of rebalancing cascades on the net demand for individual assets will look like noise, even if the flows are fully rational (view Market noise[208]). Predictions of aggregate flows become infeasible because of alternating buy and sell orders, feedback loops and threshold-based execution rules. This cautions against just dismissing seemingly non-fundamental market flows as irrational and betting against them.

Benchmarking

The most common motive of rules-based rebalancing is benchmarking, i.e. the use of pre-set standards for allocation, risk, and return. Many investment managers are formally or informally benchmarked against some market index and prefer to contain deviations of their returns from those of the benchmark index.

"Underweights" in volatile but outperforming assets are the main risk of violating these margins because such assets simultaneously outperform and gain weight in the benchmark. Hence, investment managers often find themselves compelled to buy overpriced and risky assets merely to contain streaks of underperformance (view Inefficient benchmarking and trading opportunities[209]). Profit maximizing traders can exploit the market's proclivity to overvalue high-beta and high-volatility assets on these occasions. Empirical research has provided evidence for a "low risk effect" in financial markets, i.e. the recurrent outperformance of low-risk versus high-risk assets, once both are scaled by volatility (view The "low-risk effect" in financial markets[210]).

Benchmark effects

Benchmarking effects should not be confused with benchmark effects. Benchmark effects arise from changes in global securities indices that are commonly tracked by investment managers. In particular, the surge in passive investment means that a large share of institutional investors is under obligation to buy and sell in accordance with the constituents and weights used by benchmark indices, regardless of assets' fundamental values (view Passive investment vehicles and price distortions[211]).

Benchmark companies revise indices regularly, causing re-weighting of sectors or countries that is not in proportion to market capitalization. Sovereign credit rating changes, for example, can establish or remove the eligibility of a country's securities for inclusion in benchmark indices. There is empirical evidence that these changes induce sizable portfolio re-allocations and international capital flows, entailing an outperformance of 'upgraded' assets at the time of announcement and the time of actual index adjustment (view A primer on benchmark index effects[212]). Upgrading here does not mean necessarily better asset quality, but rather the assets' greater access to index-tracking capital allocations.

Regulatory effects

Regulatory changes can necessitate the strategic rebalancing of large segments of the market. This motive is particularly important for tightly regulated institutions such as insurance companies and pension funds (view Pension funds and herding[213]). Thus, the EU reform of the regulation and supervision of insurance and reinsurance undertakings in 2016 introduced bias against assets with high market and liquidity risk, such as equity, and in favor of low-yielding sovereign bonds (view The global systemic consequences of Solvency II[214]). Also, regulatory changes seem to be one of the key motivations behind herding in the pension industry. Greater complexity and policy-maker discretion in the wake of the great regulatory reform of the 2010s means that investment managers must pay more attention to regulatory policies, not unlike the way they have monitored monetary policies (view How bank regulatory reform has changed macro trading[215]). Since regulatory allocation changes are unrelated to risk-return optimization resultant flows are likely to be inefficient and conducive to price distortions.

ETFs

Exchange-traded funds are hybrid investment vehicles that are continuously traded in a liquid market. The goal of a traditional ETF is to match the returns of its associated index or market sector. ETFs have been a major part of the passive investment boom since the 2000s, expanding in size, diversity, scope, and complexity (view The passive investment boom and its consequences[216]).

All ETFs rebalance periodically. A regular passive ETF weights its holdings in a fashion that is similar to the underlying index but might rebalance only on an annual or semi-annual basis. Such rebalancing may lead to just subtle market price distortions. Rebalancing flows can become a stronger force when the arbitrage mechanism between ETFs and their constituent securities runs into trouble. ETF prices can deviate significantly from those of the constituent securities, especially at high frequencies, for illiquid assets and during periods of financial stress. Empirically, ETFs have been associated with greater co-movement of asset prices: stocks tend to co-move more with their respective indices once they are included in ETF portfolios. There is also evidence that ETFs are associated with increased price volatility of the constituent securities (view Can ETFs contribute to systemic risk?[217]).

Rebalancing flows of equity ETFs that are leveraged can be particularly conducive to price distortions. The goal of leveraged ETFs is to realize returns that may be double or triple those of the underlying index or market sector. Leveraged ETFs use borrowed money to increase returns. Leveraged ETFs are subject to automatic rebalancing rules, requiring them to buy when prices rise and sell when they fall. As leveraged ETFs have become a significant factor in U.S. equity markets, they can reinforce or even escalate large directional moves in the stock market, both through their own transactions and other market participants' front running (view The dangers of leveraged ETFs[218]).

Equity parity

More subtle rebalancing flows arise from the so-called "uncovered equity parity". This parity suggests that when foreign equity holdings outperform domestic U.S. holdings, USD-based investors are exposed to elevated exchange rate risk and country risk in the form of higher USD notional in the foreign currency area. There should be a tendency to reduce or hedge the exposure subsequently. There is indeed empirical evidence for investors selling winning equity markets in

1990-2010 (view The idea of uncovered equity parity[219]). However, other analyses suggest that this effect may not be dominant overtime (view Examining the uncovered equity parity in the emerging financial markets[220]). Plausibly, equity parity flows introduce subtle short-lived distortions around rebalancing dates.

Constant Proportion Portfolio Insurance

Constant Proportion Portfolio Insurance or CPPI products are capital protection products. Rather than using options, they deploy a dynamic asset allocation strategy. Put simply, a CPPI strategy allocates between a riskless asset and a risky asset, such as equity, hedge funds, or commodity indices. The manager defines the "cushion" or the percentage of the fund's assets that may be put at risk, which is estimated based on the difference between the initial value of the product and the present value minimum necessary to provide the capital guarantee at maturity.

In rising markets, a CPPI strategy allocates more towards the risky asset. In a falling market, it allocates more towards the safe asset. Since CPPI flows do not consider any aspects of assets' fundamental value, they are an example of inefficient flows that reinforce market trends.

High-frequency trading

High-frequency traders do not really rebalance, but also follow strict rules-based position management. High-frequency trading became a large-scale business during the 2000s and is managed mostly by independent proprietary traders. It executes large numbers of trades in less than one millisecond, powered by trading algorithms and based on fast-moving market data. The share of high-frequency trading across various markets has been estimated between 10% and 50%. Most high-frequency strategies seek to exploit tiny arbitrage opportunities in large volumes. For example, in "slow-market arbitrage", the high-frequency trader detects price moves on one exchange and picks off orders sitting on another before it can react. High-frequency trading strategies respond at high speed to changes in prices by using relatively simple strategies. Speed, rather than reflection, is of the essence. In particular, high-frequency trading algorithms have no fundamental anchor and simply move too fast for humans to intervene with judgment. For example, when stocks drop, even if due only to a "fat finger", the programs may decide to stop trading, withdraw liquidity from the market, or even aggravate the sell-off.

While high-frequency trading can provide liquidity and efficiency on many occasions, it can magnify volatility on others. In particular, it can make markets more prone to vanishing liquidity. Increases in trading speed, in conjunction with market concentration and regulatory costs of market making, augment the probability of liquidity events (view Liquidity events[221]). The May 2010 "flash crash" in the U.S. stock market exemplified that risk. Moreover, there is a non-zero probability of outright "glitches" that can escalate modest price changes toward systemically destabilizing events (view High-speed trading: lessons from quantum physics[222]). Modern physics teaches that objects behave differently as they reach the speed of light. In particular, quantum physics suggests that 'freak events' that destabilize the markets are likely to occur.

"Changes in the weights that a popular benchmark gives to different countries can trigger a similar rebalancing among the funds that track it and result in sizable movements in international portfolio allocations and capital flows."
—Raddatz, Schmukler and Williams, 2015

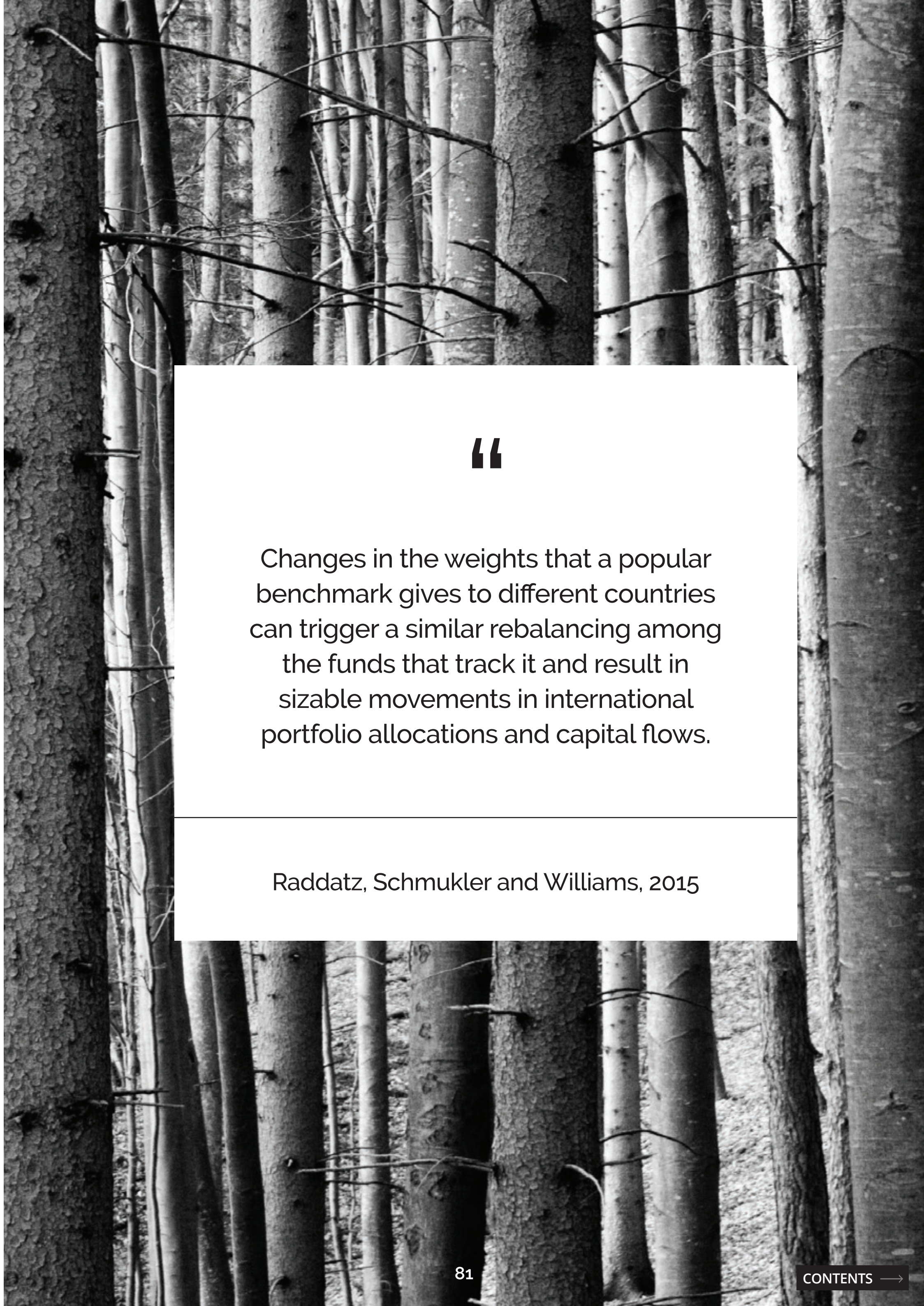
Price distortions and government intervention

Political agenda, interventions and regulation

Governments occasionally seek to instrumentalize markets for political-economic purposes, such as affordable housing, currency undervaluations, or financial conditions-driven economic expansions. Resulting legislation, regulations, and interventions can have both intended and unintended consequences.

– The most common example is government policies that influence interest rates. The dominant influence of central banks over short-term rates is well known, but since the global financial crisis both monetary and regulatory policies also seem to have played an important role in the compression of term premia (view How Fed asset purchases reduce yield term premia[223]), liquidity risk premia, and credit risk premia. The pervasive influence of government policies over yields at all maturities arises not only from their direct influence on demand and supply but also from their repercussions on the functioning of markets. This makes the valuation of many assets highly dependent on the underlying policy agenda. Doubts regarding this agenda could lead to disruptive re-pricing of duration risk (view The dangers of ultra-low interest rates in Europe[224]). Note that duration risk has a great bearing on many other financial claims, particularly low-beta high-quality stocks. The concept of equity duration represents stocks' sensitivity to long-dated discount factors (view Why and when "equity duration" matters[225]).

– Financial laws or rules can severely impair liquidity and the functioning of markets. A drastic case would be the introduction of financial transactions taxes, which has been discussed for some time in developed markets (view Europe's financial transaction tax and the consequences[226]). A more subtle example of secondary unintended consequences is the effect of cheap financing and capital controls in China on demand for physical metals (view China's commodity financing deals[227]).
– Government interventions often seek to "manage" a fundamental trend rather than stop or reverse it. The classic example is currency interventions, which often serve to "control volatility" or to temper the pace of appreciation or depreciation. When central banks "lean against the wind" with sterilized interventions, they create a combination of price inertia and carry opportunity (view Explaining FX forward bias[228]), enhancing the profitability of FX carry trades. Moreover, price distortions arise from the fear of the announcement or execution of the intervention. Value generation along the fundamental trend can resume after the intervention has been implemented (view The limited effect of FX interventions[229]).



CONTENTS

– Financial regulation can lead to unintended price distortions. For example, the regulatory reform in the European life insurance industry ("Solvency II") has enhanced the importance of market-based discount factors of the liabilities of some of the largest global bond investors. This has accentuated the tendency of declines in (already low) long-term bond yields to escalate in feedback loops as a consequence of large mechanical hedging flows with little consideration of fundamental asset value (view Understanding duration feedback loops[230]).

"Other things equal, lower interest rates make it easier to sustain or decrease debt, and require a more limited fiscal consolidation." —Blanchard, Furceri and Pescatori, 2014

5.4 Endogenous market risk

Endogenous risk refers to uncertainty regarding the interaction of financial market participants, as opposed to uncertainty about traded assets' fundamental value. Endogenous market risk often manifests as feedback loops after some exogenous shock hits the market. An important type is setback risk, which refers to the asymmetry of the upside and downside potential of a trade that arises from market positioning. Setback risk is a proclivity to incur outsized mark-to-market losses even if the fundamental value proposition of the trade remains perfectly valid. This makes it the natural counterweight to popular positioning. A useful two-factor model for detecting setback risk can be based on market positioning and exit risk. There are quantitative metrics for both. The highest setback risk is characterized by crowded positions that face an incoming type of shock that most investment managers have not considered. This section is based on the blog Endogenous market risk[231].

Basic points

What is endogenous market risk?

Endogenous market risk is the risk generated and reinforced within the financial system by the interaction of its participants. This is opposed to exogenous risk, which refers to shocks that come from outside the financial system, such as changes in fundamental asset values or political events. The term endogenous risk was coined by researchers at the London School of Economics (LSE) and is the focus of the LSE's Systemic Risk Centre[232].

A key propagation mechanism of endogenous market risk is feedback loops: one trader's losses and liquidation often trigger another trader's risk reduction and so forth. Risk management, balance sheet constraints, and publicity can all act as amplification mechanisms. Importantly, the actively trading part of the market is not a zero-sum book but often it jointly bets on the growing financial wealth of the world or it takes positions that are implicitly subsidized by non-financial institutions. The habitual focus of most professional traders on flows and positions testifies to the critical importance of endogenous market risk for short-term price action.

What is setback risk?

Setback risk is a particularly important form of endogenous market risk. Technically speaking, it represents the difference between downside and upside risk

to the mark-to-market of a contract due to investor positioning. Like all endogenous risks, it is in itself unrelated to the fundamental value of the underlying assets. If an investor believes that a security is fundamentally overvalued and may be repriced in the future, this is not an endogenous market risk, but merely a disagreement with the prevailing market valuation.

Setback risk indicates the market's latent tendency to revert to a state where positions are "cleaner", meaning less crowded or reliant on leverage. Importantly, such risk arises merely through the "crowdedness" of trades and their risk management, irrespective of whether the fundamental value proposition is good or not. In fact, it is often the trades that offer the highest and most plausible long-term expected value that are subject to the greatest setback risk. This is consistent with a negative skew in the returns of popular risk premium strategies. For example, FX carry trade returns have historically displayed a proclivity to much larger negative than positive outliers (view FX carry trade crashes[233]), even when they remained profitable in the long run.

Setback risk in trading practice

Setback risk is the natural counterweight to popular positioning motives, such as implicit subsidies, fundamental trends or statistical trend-following. It results from the "crowdedness" of trades. A crowded trade is a position with a high ratio of active institutional investor involvement relative to its liquidity. Crowding comes with excess expected returns but typically skews risk to the downside. The popularity and crowdedness of trades should be justified by a sufficient risk premium. Therefore, complementary setback risk measures can often improve systematic strategies that rely on popular factors.

Setback risk also ties the prospects of popular presumed market-neutral strategies to the state of overall market risk prices. When risk-off shocks hit the dominant directional exposure of financial market participants, their capacity to maintain other positions also decreases. Hence, all crowded and popular positions are exposed, even if they have no significant historical market beta. For example, there is empirical evidence that momentum strategies that buy winners and sell losers in terms of recent price trends have greater sensitivity to the downside than to upside market risk across asset classes (view Momentum trading and setback risk[234]).

Generally, the presence of endogenous market risk has profound consequences on trading returns across many valid trading styles and systematic strategies. This risk is hard to avoid and skews the probability of future price moves against valid positioning motives as long as these motives are common to a significant part of the market. Mechanical risk reduction rules and market liquidity constraints also suggest that the distribution of returns will have "fat tails". Put simply, large adverse outliers relative to standard deviations should be expected in most value-generating trading strategies.

Clues

Information on endogenous market risk comes from a wide variety of sources, including positioning data, short-term correlation of PnLs with hedge fund benchmarks, asymmetries of upside and downside market correlation, or simply past performance and the popularity of trades in broker research recommendations. Endogenous market risk of relative value and arbitrage trades often arises from outflows in the hedge fund industry. Hedge funds' capital structure is vulnerable to market shocks because most of them offer high liquidity to loss-sensitive investors (view A theory of hedge fund runs[235]). Moreover, the build-up of endogenous market risk can be inferred from theory. For example, compressed interest rate term premia at the zero lower bound for policy rates are naturally quite vulnerable to any risk of future rates increases (view Term premia in the times of "lift-off"[236]). Finally, macro indicators such as external balances and international investment positions indicate the financial exposure of the global economy at large to various currency areas.

A two-factor model for detecting setback risk

The idea

It is useful to decompose setback risk into two factors: positioning and exit risk. Positioning refers to the "crowdedness" of a trade. Exit risk refers to the probability of liquidation, i.e. that the crowd will run for the exit. Setback risk is high when a trade is "crowded" and near-term position reductions are probable. While the positioning component always relates to a specific contract, exit risk can be a global factor, such as tightening dollar funding conditions.

"In an unfolding crisis, most market participants respond by liquidating their most liquid investments first to reduce exposures and reduce leverage."
—Myron Scholes, 2000

Positioning

Positioning relative to market liquidity principally indicates the potential size of the PnL setback. For some contracts, exchanges or custodian banks provide outright positioning data. However, these are not always easy to interpret. In practice, macro traders pay much heed to informal warning signs, such as anecdotal evidence of positioning provided by their brokers, surveys among investment managers, return correlation with market benchmarks (view Understanding market beta in FX[237]) and lack of position performance in spite of positive news. Also, the medium-term historic performance of popular risk premium strategies is often a good indirect indicator of their popularity and, hence, positioning. For some popular algorithmic strategies, such as trend following, positioning can be estimated based on the replicated stylized position signals and the size of assets managed under this type of strategy (view Estimating the positioning of trend followers[238]).

Conceptually, the crowdedness of trades in a portfolio can be measured by "centrality", a concept of network analysis that measures how similar one institution's portfolio is to its peers (view Crowded trades: measure and effect[239]). Empirical evidence suggests that the centrality of portfolios is negatively related to future returns. Positioning can also be inferred from the economic newsflow. Cognitive biases may systematically bias positioning towards the latest "surprises" or publicized changes in major economic indicators, even if those are unstable and not a proper measure of underlying trends (view Reported economic changes and the Treasury market: impact and payback[240]).

Exit risk

Exit risk principally indicates the probability of a near-term setback, be it small or large. The most prominent triggers of large-scale unwinding of macro trades are volatility or Value-at-Risk jumps (view Quantitative easing and "VaR shocks"[241]) and liquidity and funding pressure (view Some stylized facts of FX liquidity[242] and Understanding global liquidity[243]). The term trigger here refers to an endogenous market shock that is likely to lead to subsequent escalatory price dynamics. Catching such triggers requires estimation of [1] the complacency of the market with respect to an adverse shock and [2] the gravity of specific adverse shocks.

Complacency here means a lack of resilience to adverse shocks. This lack of resilience arises from an optimistic mode of expectations, maybe fueled by positive publicity for assets and trades or by implausibly low-risk perceptions that are likely to be revised upward during the lifetime of the trade, even if the risk itself does not manifest. Risk perceptions can be measured in a wide range of news-based, survey-based and asset price-based indicators (view The 1×1 of risk perception measures[244]). Direct measures of complacency include variance risk premia (view What variance swaps tell us about risk premia[245]) and the term structure of option-implied equity volatility (view VIX term structure as a trading signal[246]). Asset return expectations of retail investors can be estimated based on demand for various types of leveraged or inverse ETFs (view Tracking investor expectations with ETF data[247]). Another plausible indication for complacency is the homogeneity of economist forecasts. Empirical analyses point to an important principle: when economists are clustered tightly around a consensus, actual data surprises tend to have a stronger market impact (view When economic data surprises matter most[248]). Generalizing this point, it seems plausible that a strong analyst consensus that supports a macro position makes this position more vulnerable to data surprises.

Gravity of shock refers to the probability that a shock is rated as significant and consequential by market participants. This depends upon the type and strength of the shock. Note that the shock itself can be exogenous (come from outside the market) but is evaluated due to its potential for unleashing escalatory endogenous market dynamics.

– One of the most toxic types of shock is a "black swan", an event that has been rated as highly unlikely, has extreme impact and is incorrectly rationalized even after it occurred. Put simply, the less probable a negative shock, the harder its impact. The worst market crises are the ones that investment managers have never prepared for (view Why decision-makers are unprepared for crises[249]).

– Another particularly dangerous type of shock is a decline in liquidity or capital ratios of financial intermediaries. This type of shock diminishes the capacity of dealers to warehouse the net risk position of other market participants. The result can be forced liquidations that put particular pressure on risk positions that offer high expected long-term value or that are popular for other reasons.

CONTENTS ⟶

– A more frequent shock with escalatory potential is a surge in people's fear of disaster. Theoretical research shows that a re-assessment of beliefs towards higher disaster risk triggers all sorts of uncertainty shocks, for example, with respect to macro variables, company-specific performances and other people's beliefs (view The power and origin of uncertainty shocks[250]). This can derail both directional and relative value trades.

Nowadays, there is a broad range of measures tracking market risk and uncertainty (view Measures of market risk and uncertainty[251]). Risk refers to the probability distribution of future returns. Uncertainty is a broader concept that encompasses ambiguity about the parameters of this probability distribution. Changes in risk and uncertainty measures indicate the gravity of shocks.

From a statistical angle, escalating shock detection often focuses on "volatility surprises" (market price changes outside the range of expected variation) that make investors revise the probabilities for various risks drastically. Volatility shocks typically draw attention to previously underestimated risks and transmit easily across markets and asset classes (view Volatility surprises[252]). Moreover, volatility shocks are critical in a statistical sense because financial returns plausibly have "fat tails". This means that [1] financial returns have a proclivity to extreme events and [2] the occurrence of extreme events changes our expectations for uncertainty and risk in the future significantly (view The dangerous disregard for fat tails in quantitative finance[253]). Such a reassessment may take days or weeks to complete and give rise to negative trends. It is important to discriminate between medium-term volatility trends and short-term volatility spikes. Longer-term changes of volatility mostly reflect risk premiums and hence establish a positive relation to returns. Short-term swings in volatility often indicate news effects and shocks to leverage, causing a negative volatility-return relation. (View Modelling the relation between volatility and returns[254]).

6 How to establish a proof of concept for a macro trading strategy

This chapter is a condensed guide on best practices for developing systematic macro trading strategies with links to related resources. The focus is on delivering proofs of strategy concepts that use direct information on the macroeconomy. The critical steps of the process are [1] downloading appropriate time series data panels of macro information and target returns, [2] transforming macro information states into panels of factors, [3] combining factors into a single type of signal per traded contract, and [4] evaluating the quality of the signals in various ways. Best practices include the formulation of theoretical priors, easily auditable code for preprocessing, visual study of data before and after transformations, signal optimization management with statistical learning, and a protocol for dealing with rejected hypotheses.

A quick, standardized and transparent process supports integrity and reduces moral hazard and data mining. Standard Python data science packages and the open-source Macrosynergy package provide all necessary functionality for efficient proofs of concept. Please view How to build a macro trading strategy (with open-source Python)[1].

Macro strategies and the importance of a proof of concept

The term "**macro strategy**" here refers to a trading strategy that systematically uses information on the macroeconomy, as opposed to company information, trader positioning, or short-term price anomalies. Macroeconomic information can be inferred from market prices (indirect approach) or information states of reports on economic activity (direct approach). If the latter is used, we can call it a "macro-quantamental strategy". In this chapter, we assume that signals are at least partly "macro-quantamental". There are two types of macro-quantamental strategies:

– **Feature-based strategies** focus on a single macroeconomic concept, such as growth or inflation changes and apply a point-in-time data series to trade one or more financial contracts systematically. For example, a single proxy of the state of the business cycle can serve as a trading signal for equity, fixed income and foreign exchange strategies (view Macroeconomic cycles and asset class returns[2]).
– **Target-based strategies** focus on a single class of financial market position, such as equity index futures or sovereign credit default swaps and apply a set of plausible conceptual macro factors for systematic trading. For example, multiple conceptual macro factors can support the trading of FX forwards in developed and emerging markets, diversifying performance across both factors and currencies (view Pure macro FX strategies: the benefits of double diversification[3]).

The **proof of concept** of a macro-quantamental strategy is conclusive empirical evidence that a trading signal and the underlying method of its creation would have delivered significant predictive power and material risk-adjusted returns. This proof is critical for deciding if an idea is worth the allocation of capital and the time and money that is required to set up a trading algorithm (or trader support tool). A valid proof of concept typically requires that we proceed in three steps as set out in Figure 6.1.

Most importantly, a valid proof of concept needs integrity. It is easy to let the three-stage process degenerate into data mining by adjusting theory and signal calculation to optimize signal quality metrics.

Statistics of predictive relations and backtested PnLs that are derived in this way have no value. Instead, they mislead risk allocation. To support integrity, the process for proofs of concept should be standardized, quick, and auditable. Long projects invite attachment to results and the temptation to torture the data for false evidence. The practices explained in this chapter place great emphasis on cutting costs and development time, thereby reducing attachment to projects and encouraging integrity.

6. How to establish a proof of concept for a macro trading strategy

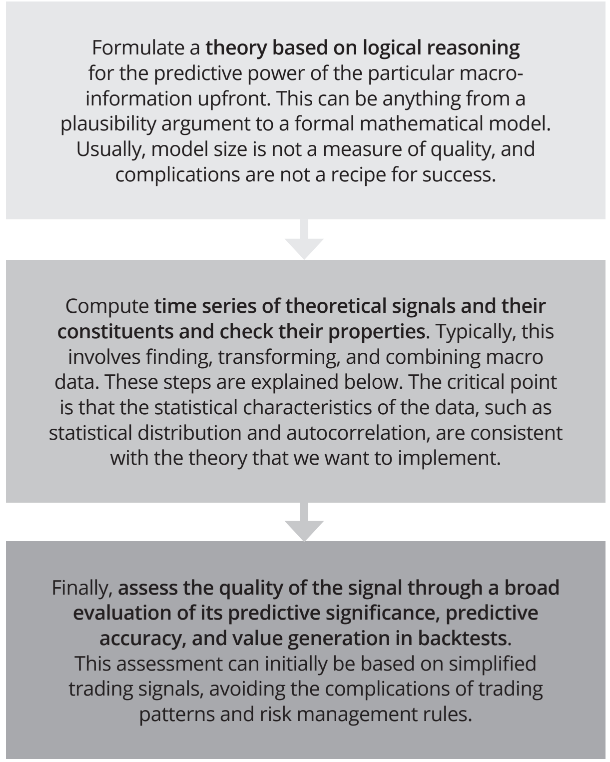


Figure 6.1: Steps for a proof of concept

A specialized open-source Python package

A proof of concept of an institutional macro trading strategy can be delivered in a standard Python environment using a handful of popular data science packages, such as pandas[4], matplotlib[5], scikit-learn[6], and the specialized Macrosynergy package[7].

The Macrosynergy package largely works on top of standard Python data science packages and provides classes and functions for the analysis and transformation of quantamental indicators, as well as for developing macro-quantamental signals and testing success with respect to predictive power and stylized PnL generation. Functionality is tailored to the formats and conventions of the J.P. Morgan Macrosynergy Quantamental System (JPMaQS), i.e., daily time series of information states across multiple markets or countries. Principally, the functions can also be applied to market and alternative data in the same format.

The Macrosynergy package shifted to version 1.0 in November 2024. It can be found on GitHub[8]. It has a stable updating documentation site[9] that is maintained by the Macrosynergy developer team.

CONTENTS

The Macrosynergy package contains seven subpackages (Figure 6.2):

download	Functionalities for downloading JPMaQS data from the J.P. Morgan DataQuery API in a convenient pandas format.
panel	Various functionalities for running calculations, analyses, and visualizations on JPMaQS Quantamental data frames, operating on panels of multiple markets or countries.
learning	Functions and classes to assist the creation of machine learning solutions with macro-quantamental data. Currently, the functionality is built around integrating quantamental data formats and scikit-learn.
signal	Various functionalities for analyzing, visualizing, and comparing the relationships between panels of trading signals and panels of subsequent returns.
pnl	Classes and functions to translate trading signals and generic daily return series into proxy profit-and-loss time series, together with visualizations and evaluation statistics.
management	Core utilities and functions, such as data frame operations, data simulations or data validations, that are used in other parts of the package or as standalone convenience functions.
visuals	Functions for visualizing quantamental data. It is built around the ability to create quick generic plots of data and provide a framework for developing custom plots.

Figure 6.2: Structure of the Macrosynergy package

Finding macro-quantamental data

Generally, macro trading signals rely on price data, flow data, alternative data, and macro-quantamental data. The first three have been staples of systematic trading for some time. This chapter focuses more on macro-quantamental information, which has traditionally been the domain of discretionary trading and only recently began transforming systematic macro trading (view How macro-quantamental trading signals will transform asset management[10]). It is essential to clarify some terminology first:

– A **macro-quantamental indicator** is a metric that combines quantitative and fundamental analysis of the macroeconomy, such as an inflation trend or a government balance-to-GDP ratio. Values must be point-in-time information states, i.e., reflect that state of public knowledge at a timestamp. Here, public knowledge does not mean that everybody actually knew, but that everybody could have known based on the available data.

– A **macro-quantamental category** is a panel of a macro-quantamental indicator for a set of countries and markets. For example, real-time annual GDP growth estimates across countries constitute a category. Validation of trading strategy principles often relies on categories rather than single indicators to enhance, drawing on the diverse experiences of multiple countries.

– A **macro-quantamental factor** is a combination of macro-quantamental indicators or categories. The combination is presumed to serve as a predictor of financial contract returns. For example, growth rates of various measures of economic activity may be combined into an "excess activity growth" factor, which is relevant to the performance of fixed-income or equity markets.

– Finally, a **macro-quantamental signal** is a combination of macro-quantamental factors and possibly other types of factors. The signal is designed to govern risk and positioning in a specific market. For example, an excess activity growth factor and an excess inflation factor in conjunction with real interest rates may be combined into a fixed-income trading signal.

At present, the primary source of macro-quantamental indicators for financial market research is the J.P. Morgan-Macrosynergy quantamental system (JPMaQS). Please view Chapter 4: The J.P. Morgan Macrosynergy Quantamental System for more details[11]. JPMaQS is currently structured into **six overarching "themes"** (Figure 4.4 in Chapter 4), encompassing **79 groups**, **986 quantamental data categories**, and **18,814 tickers** (as of December 2024). The latter theme actually contains approximated daily returns of a diverse range of financial derivatives and cash contracts structured in the same format as proper quantamental data to facilitate detecting predictive relationships.

The easiest way to import quantamental categories and target returns into Python is through category tickers. Combined with cross-section identifiers (standard currency symbols), they form indicator tickers that can be downloaded quickly. We can find macro-quantamental categories in one of two ways:

– **Browsing:** The section "Quantamental indicators on JPMaQS"[12] of the Quantamental Academy provides links to "books of Jupyter notebooks", ordered hierarchically by themes and then category groups. Each category group notebook contains a top section with labels, definitions, and, most importantly, tickers for downloading. For example, if we need information on the states of various manufacturing business surveys, those can be found in the theme macroeconomic trends[13], by scrolling the left-hand sidebar to manufacturing confidence scores[14]. The Jupyter notebooks also contain empirical visualizations, methodological annexes, and examples of empirical predictive relationships.

– **Search bar:** The "Quantamental indicators on JPMaQS"[15] section also contains a search bar ("Search themes") on top of the browsable windows. Entering the label of a category will bring up the documentation for all related concepts in Jupyter notebooks.

Downloading and updating macro-quantamental data

Downloading and regularly updating quantamental indicators and target returns can be managed through the Download class[16]. Instantiation of the class requires DataQuery client credentials. Actual downloads are executed using the class's download method[17]. Beyond optional parameters that limit the scope of the download, this method requires three types of information:

6. How to establish a proof of concept for a macro trading strategy

– the tickers of all categories required for building quantamental factors,
– the tickers of all target return categories that are considered, and
– the cross-sectional identifiers of the markets that are considered are mostly standard currency symbols ("AUD", "BRL", etc.). For currency symbols refer to Appendix 2.

Having collected the above pieces of information in Python lists, we can combine them into a single list of quantamental indicators tickers ("<cross-section>_<category_ticker>"). This list is passed to the download method[18], which then downloads data from the DataQuery API as time-series JSONs and then converts and wrangles the JSONs into standardized pandas data frames or "**quantamental data frames**".These "long" data frames have at least four columns containing the cross-section identifier ("CID"), an extended category ticker ("xcat"), a real-time date ("real_date"), and the actual indicator value ("value"). Other potentially useful columns contain the quality grade of an observation ("grading"), the lag to the end of the observation period in days ("eop_lag"), and the lag to the median of the observation period ("mop_lag").

The download process is exemplified in all Jupyter notebooks on the Quantamental Academy[19], including the introductory code for Trading strategies with JPMaQS[20]. Regular re-downloading of JPMaQS data is recommended, even before putting strategies in production. This is not just to capture the new observations but also the potential inclusion of older vintages as the system's archaeological dig for historic information progresses.

Visualizing features and target returns

The visual study of indicators, factors, signals, and targets is one of the most important and underestimated practices in strategy development. It is not just critical for our intuitive understanding. Visualization is also the most important legitimate part of "learning from the data", unlike data mining or hindsight.

Studying the properties of data categories and their transformations helps us to address one important question: "Do the data have basic properties that I would expect them to have according to my investment hypothesis?". In other words, we can check if actual data matches theoretical concepts and, where necessary, make adjustments rather than rushing the process by immediately testing for predictive power and PnL generation. Three types of simple visualizations are beneficial and can be quickly executed in a standardized way:

1. The visualization of historical distributions of indicator panels in an efficient, standardized form is supported by the view_ranges[21]. It plots important aspects of their distribution for multiple cross-sections and for one or more categories. Application examples can be viewed in the notebook Introduction to Macrosynergy package[22]. Key issues to check are the following:
 – The balance of distribution may reveal an unexpected bias towards long or short positions, which may indicate the need to set a more realistic neutral level.
 – Large cross-sectional differences in variation may reveal an unexpected concentration of factor and signal values in one country, which may indicate the need for better scaling across sections.
 – The pattern of outliers may reveal a proclivity to extreme values in both directions ("high kurtosis") or in one direction ("skewness"), which may indicate the need for winsorization ("capping" or "flooring") of extreme values to contain the influence of distortions and to avoid inordinate intertemporal risk concentrations.

2. The visualization of indicator timelines across sections is delivered in a standard format by the view_timelines[23] function. It displays panels of timelines across sections, potentially across indicators. Application examples can be viewed in the notebook Introduction to Macrosynergy package[24]. Importantly, these timeline facets inform on the speed of factor adjustment and the frequency of position flips, both of which are critical for transaction costs. Many quantamental factors imply gentle position adjustment, but some factors that are based on short-term changes in information states may produce large daily or weekly position changes (view Macro information changes as systematic trading signals[25]). The point is to check if the volatility of factors matches expectations with respect to the desired characteristics of a strategy.

3. Finally, the visualization of correlations of categories or across sections is quickly executed through the correl_matrix[26] function. Application examples can be viewed in the notebook Introduction to Macrosynergy package[27]. The correlation matrices inform on two important aspects of diversification: diversification across countries or markets and diversification across factors. High correlation across countries and factors means that, at least historically, performance has been dominated by a single global factor.

These visualizations and checks should be applied at all stages where new categories are downloaded or calculated. They should also be applied to target returns, checking the distribution of returns, concentration of performances across time, and diversification benefits of positioning across countries or markets.

Transforming quantamental categories into quantamental factors

Macro-quantamental categories are like Lego blocks rather than ready-to-deploy factors. Typically, one must transform and combine categories to arrive at factors and signals. The Macrosynergy package supports transformations with various convenience functions that operate transparently on panels rather than individual indicators. In practice, transparency and reliability often trump complexity.

– General operations on category panels can be managed by the panel_calculator[28] function of the Macrosynergy package. It uses an easily readable argument, i.e., a formula in text format, to execute transformations for full panels. This function is very flexible and saves a lot of code. Beyond simplification, the main benefit is that operations are easily auditable, reducing gross errors when calculating factors and signals. The text string that governs the operation can contain mathematical operations and Python operations that apply to a pandas panel data frame, i.e., a data frame with time as a row index and cross-sections as a column index. Examples and details of this "workhorse function" can be viewed in the related section of the notebook Introduction to Macrosynergy package[29].

– The make_zn_scores[30] function specializes in the time-consistent normalization of categories of information states. This type of transformation is particularly important for modifying the distribution of data panels and is a standard preparatory step before summing or averaging categories with different units or orders of magnitude. The function computes z-scores for a category panel based on sequential updating mean absolute deviations and a specified neutral level that may be different from the mean. The term "zn-score" refers to the normalized distance from a neutral value. Setting the right neutral value for quantamental factors is crucial to avoid undue long or short biases. Application examples of this function can be viewed in the related section of the notebook Introduction to Macrosynergy package[31].

– Finally, the calculation of relative category values across countries or markets can be delegated to the make_relative_value[32]. It generates a data frame of relative values for a given list of categories. In this case, "relative" means that the original value is compared to a basket average. The basket can be a set of cross-sections of the same category. By default, basket averages do not require the full set of cross-sections to be calculated for a specific date but are always based on the ones available at the time. This may change the characteristics of relative series over time but preserves valuable information and efficiently uses imbalanced panels. Application examples can be viewed in the related section of the notebook Introduction to Macrosynergy package[33].

For clarity of analysis and usage of statistical learning, it can be advantageous to define all trading factors such that their presumed predictive relation with target returns is positive. For example, this helps filter our factors whose past direction relation has been contrary to theory, for example, by use of non-negative least squares.

Combining macro-quantamental factors into signals

Using economic theory and conceptual parity

Most macro-quantamental strategies combine multiple factors into a single trading signal. This partly reflects that the influence of a single macro concept can be quite seasonal, i.e., concentrated on certain time periods. For example, inflation plausibly influences equity markets mostly when it is far from the central bank's target and triggers a significant policy response. Combining diverse macro-quantamental factors into one signal broadens the origin of value generation and, typically, reduces the seasonality of PnLs.

There are two basic ways to combine conceptually different factors: mathematical operations and statistical learning. This sub-section deals with the mathematical operations. They come in two flavors: logical combinations and conceptual parity. Both methods are simple but often quite robust out-of-sample, as they rely on plausibility and logic rather than specific past experiences.

– Logical combinations rely on economic theory. For example, if we assume that excess economic growth and inflation both influence interest rates and that the influence of inflation is twice as strong as the one for growth, our factor is just "1/3 x growth + 2/3 x inflation". For data panels, these operations are best done using the panel_calculator[34].

– Conceptual parity combines panels of factors by normalization and subsequent averaging. Thus, after adjusting factor values by standard deviations from neutral levels, this method gives each concept the same weight. For example, if inflation and credit growth are both viewed as individually relevant predictors of bond returns, conceptual parity would give each the same importance in the signal calculation. Although this approach is simple, it is also quite robust to economic change and impedes implicit or explicit hindsight bias. Success mainly relies on clearly separating different types of economic influences. For example, inflation and growth are typically separate influences on markets, even if, over a specific stretch of history, they were correlated. By contrast, different types of CPI inflation rates are not separate concepts, even if their correlation is imperfect. If there are strong theoretical priors that one concept is more important than another, conceptual parity can use weighted averages.

Conceptual parity calculations are efficiently managed with the make_zn_scores[35] and linear_composite[36] functions of the Macrosynergy package. The latter is designed to calculate linear combinations across categories under clearly stated rules. It can produce a composite even if some of the categories are missing. This flexibility is valuable because it enables one to work with the available information rather than discarding it entirely.

Mathematical combinations come with a health warning: once an initial hypothesis has been formed, one must not "play around" with the formulas to obtain better backtested PnLs. This would be plain old data mining. By contrast, it is legitimate to revise signals if they reveal logical inconsistencies or unexpected behavior. Simply put, mathematical factor combinations must steer clear of optimization, which would easily degenerate into data mining and invalid backtests. All optimization should be performed through a sequential statistical learning method, as explained in the next sections.

Using statistical learning

When theoretical priors on macro-quantamental factors are scant or fuzzy, statistical learning is a more suitable method for signal computation. This path also allows developers with little experience in economics to generate good signals by using a broad range of vaguely relevant categories and a suitable learning process. Statistical learning offers methods for sequentially choosing the best model class and other hyperparameters for signal generation, thus supporting realistic backtests and automated operation of strategies. The main purposes of such statistical learning are factor selection, return predictions, and market regime classification (view Optimizing macro trading signals – A practical introduction[37]).

The workhorse Python class for statistical learning in macro-quantamental strategy development is SignalOptimizer[38] of the Macrosynergy package. It manages sequential model selection, fitting, optimization and forecasting based on quantamental panel data. It works on top of scikit-learn but, unlike that package's standard functions, respects the panel structure of features and target returns. Optimization is governed by the calculate_predictions[39] method, which uses a grid of models and hyperparameters, a cross-validation pattern, and a performance criterion for executing any of three jobs:

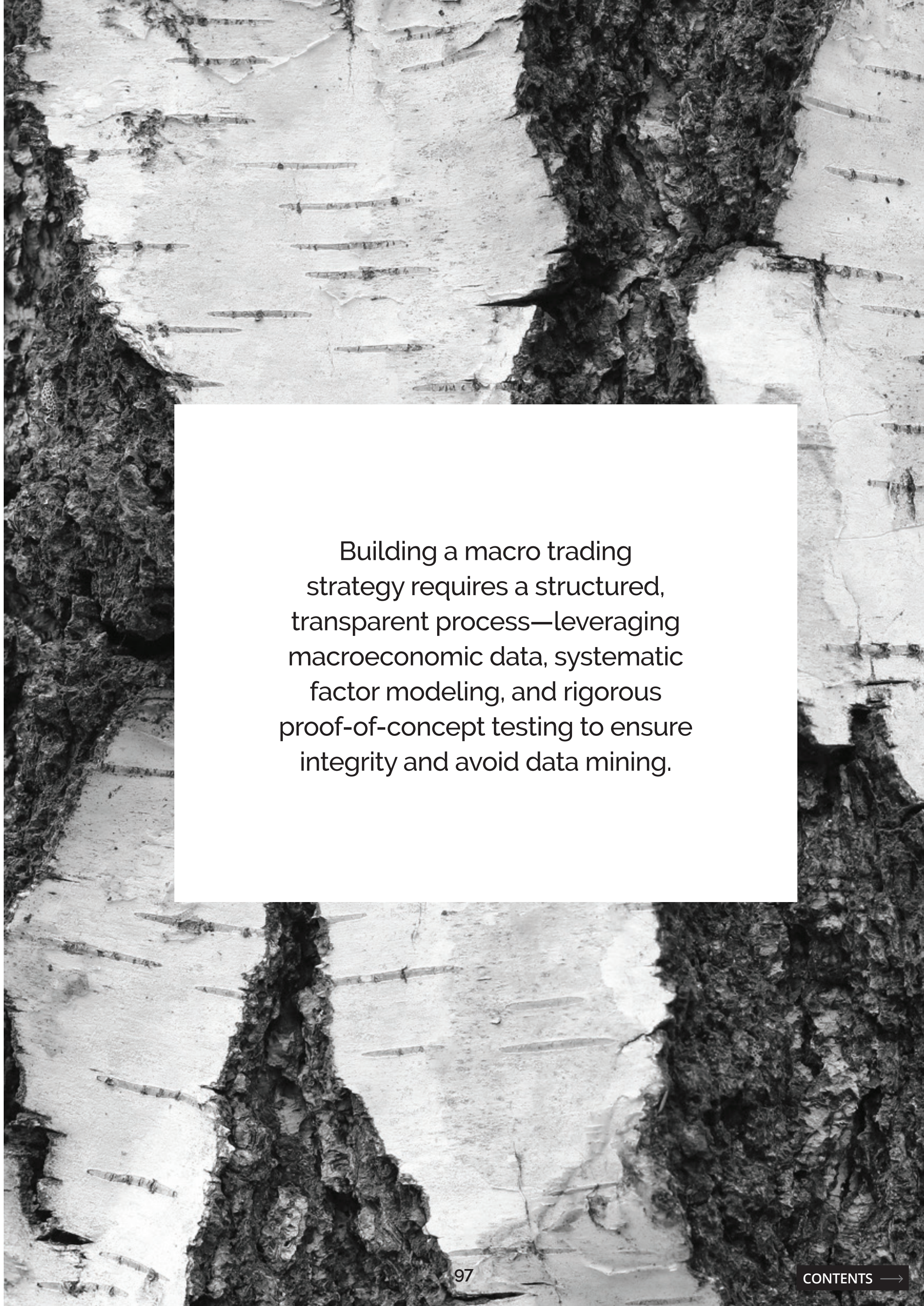
– Sequentially selecting constituent categories for a composite signal from a set of candidates,
– Sequentially selecting and applying regression models for translating a chosen set of factors into a single return prediction, which is a valid basis for a trading signal.
– Sequentially selecting and applying classification models to detect favorable or unfavorable regimes for the target returns of a strategy.

Regression-based learning is a particularly important and intuitive method for combining quantamental factors into trading signals. The learning process optimizes model parameters and hyperparameters sequentially and produces signals at each point in time based on the regression model that performed best up to that date. The process learns from growing datasets and produces point-in-time signals for backtesting and live trading (view FX trading signals with regression-based learning):[40]. Two "add-ons" to standard regression should be considered:

– Simple regression-based predictions disregard statistical reliability, which tends to increase as time passes or decrease after structural breaks. It is, therefore, advisable to adjust signals by the statistical precision of parameter estimates (view How to adjust regression-based trading signals for reliability[41]). The adjustment correctly aligns intertemporal risk-taking with the predictive power of signals.
– A helpful auxiliary technique in statistical learning is dimensionality reduction with Principal Components Analysis (PCA) (view Using principal components to construct macro trading signals[42]). It condenses the key information from a large dataset into a smaller set of uncorrelated variables called "principal components." This smaller set often functions better as features for predictive regressions, stabilizing coefficient estimates and reducing the influence of noise.

Qualified statistical learning requires attention to the bias-variance trade-off of machine learning, i.e., the balance between a process's ability to generalize to unseen data (low variance but potentially high bias) and its ability to accurately fit the available data (low bias but potentially high variance). Statistical learning for macro trading signals has a less favorable bias-variance trade-off than many other areas of quantitative research. This means that as we move from restrictive to flexible models, the benefits of reduced bias typically come at a high price of enhanced variance. This reflects the scarcity and seasonality of macro events and regimes.

While the term variance here refers to model instability, it also leads to "unproductive signal volatility", i.e., model choice and estimation can become a major source of signal variation that logically has no relation to the variation of conditions for market performance. Hence, one typically needs to be parsimonious in delegating decisions



Building a macro trading strategy requires a structured, transparent process—leveraging macroeconomic data, systematic factor modeling, and rigorous proof-of-concept testing to ensure integrity and avoid data mining.

to statistical learning and must emphasize reasonable and logical priors. If data are scarce, simple regression methods, such as 'ordinary least squares' (OLS) and non-negative least squares, often outperform more elaborate methods, such as elastic net or decision trees (view Regression-based macro trading signals[43]).

Signal evaluation and backtesting

Meaningful evaluation of macro trading signals must consider not just backtested PnLs but also statistics that account for their seasonality and diversity across countries. In the article Evaluating macro trading signals in three simple steps[44], we presented three complementary types of evaluation, which are briefly summarized below. Conscientious evaluation of macro signals not only informs the selection process. It also paints a realistic picture of the PnL profile, which is critical for setting risk limits and for broader portfolio integration. One should have a protocol for dealing with poor signals constructively. The only real failure is the failure to acknowledge the empirical lessons.

Sometimes, lack of predictive power can be traced to logical and computational errors, such as applying incorrect neutral signal levels or combining factors incorrectly. In these cases, modification of signals is legitimate. However, if the basic trading hypothesis is clearly rejected, it is important to acknowledge the fact and, maybe, trace faults in basic reasoning or interpretation of data. Simply put, in these cases, we must either cut our losses (in terms of development costs) or go back to the drawing board. One of the most harmful habits is trying to salvage an idea by "playing around with the data", which may gravely mislead decisions of capital allocation and risk management.

Test 1: Significance of proposed predictive relations

These analyses visualize and quantify the relations between macro signals and subsequent returns across countries or currency areas. A critical metric is the significance of forward correlation, i.e., the probability that a predictive relation has not been accidental. This metric requires a special panel test that adjusts the data of the predictive regression for common global influences across countries (view Testing macro trading factors[45]). This test is a most useful selection criterion for macro signal candidates. It is important, however, that the hypothesized relation between features and targets is similar across countries and that the country-specific features matter, not just their global averages. The CategoryRelations[46] class of the Macrosynergy package is the workhorse for analyzing and visualizing the relations of multiple panel categories. Most often, it is applied to trading signals and subsequent target returns across countries or markets using the reg_scatter[47] and multiple_reg_scatter[48] methods. It allows consideration of multiple trading frequencies, blacklisted periods for cross-sections, and delays in the application of predictive information. Examples of applications of this class for two categories can be found in the related section of the notebook Introduction to Macrosynergy package[49].

Test 2: Accuracy of directional predictions

Here, statistical accuracy measures the share of correctly predicted signs or directions of subsequent returns relative to all predictions. Accuracy is more about correct classification into "good" and "bad" conditions for the traded contract than

about the strength of the relation. It also implicitly tests if the signal's neutral (zero) level has been well chosen, which is very important for PnL generation. A particularly important metric for macro trading strategies is **balanced accuracy**, which is the average of the proportions of correctly predicted positive and negative returns. This metric is indispensable if we need a signal that works equally well in bull and bear markets for the target contract.

The SignalReturnRelations[50] class from the Macrosynergy package is specifically designed to analyze, visualize, and compare the relationships between panels of trading signals and panels of subsequent returns. Its methods display various summary tables of classification performance metrics and statistical measures, along with visualizations, including accuracy ratios across various frequencies. Examples of applications can be found in the related section of the notebook Introduction to Macrosynergy package[51].

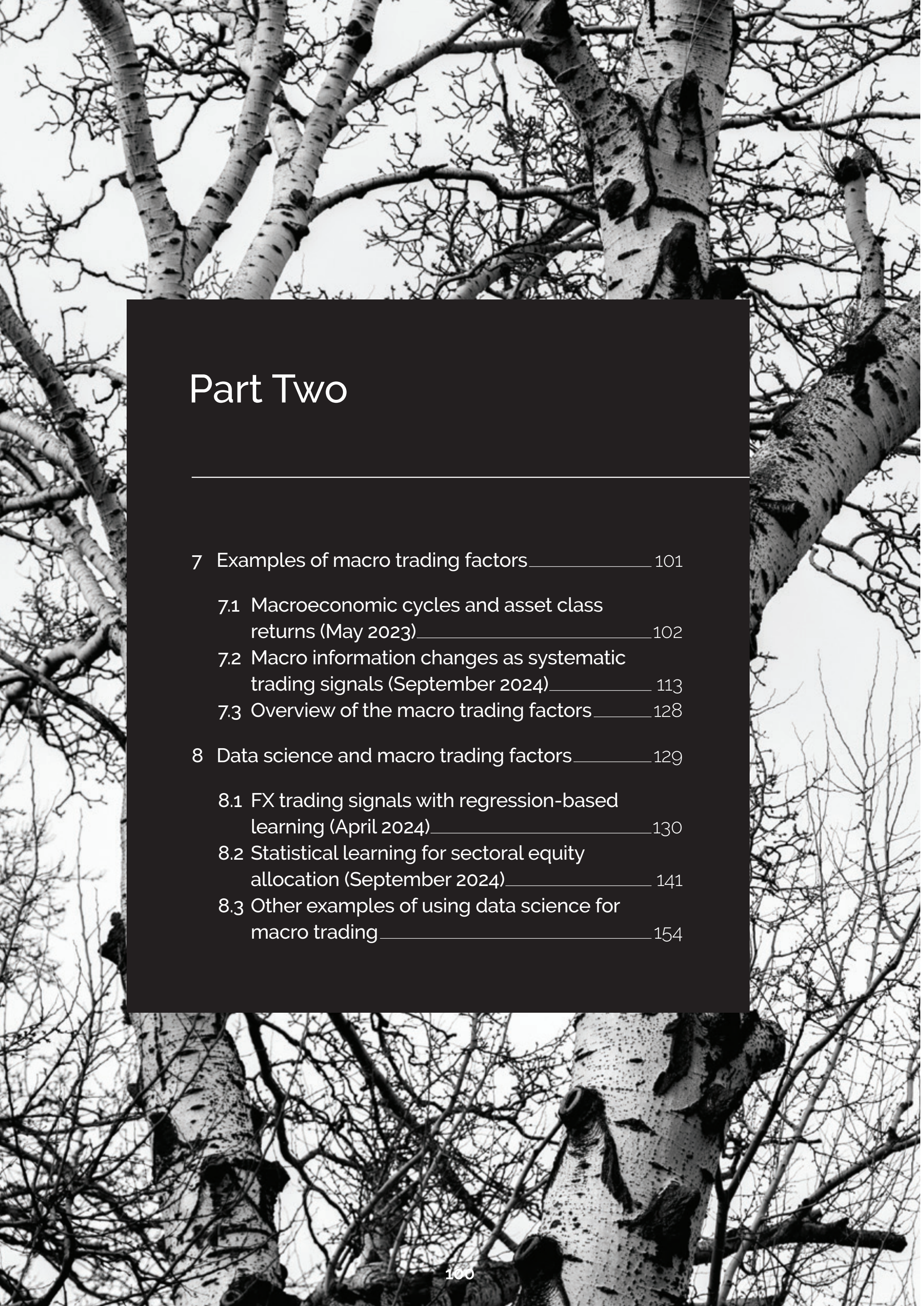
Test 3: Performance metrics of stylized PnLs

We can gauge the economic value of trading signals by simulating standardized "naïve" profit and loss series. They can be calculated using daily generic returns data, such as those provided by JPMaQS, and by applying normalized signals and regular rebalancing following previous signals to allow for trading time or slippage. Naive trading signals should be capped below extreme values, say 3 or 4 standard deviations, as a reasonable risk limit. A naïve PnL does not consider transaction costs or risk management tools. It is thus not a realistic backtest of actual financial returns in a specific institutional setting. However, it is an objective and undistorted representation of the economic value of the signals, independent of the rules, size, and conventions of the trading institution.

Standard performance metrics of naive PnL analysis should include various types of risk-adjusted returns (Sharpe, Sortino), correlation coefficients with global risk benchmarks, such as bond and equity prices, measures of seasonality, and drawdown analytics.

The NaivePnL[52] class is designed to provide a quick and simple overview of a stylized PnL profile of a set of trading signals. Its make_pnl[53] method produces a proxy daily profit-and-loss series with a limited set of options for modifying signals prior to application. The function is designed for testing, not optimization or data mining. Other methods govern visualizations of resulting PnLs and trading positions. Examples of applications of the class and its methods can be found in the related section of the notebook Introduction to Macrosynergy package[54].

CONTENTS ⟶



Part Two

7 Examples of macro trading factors

This chapter illustrates the construction of trading factors derived from quantamental indicators. The below examples and other "use cases" on Macrosynergy Quantamental Academy highlight the predictive power and economic value of macro-quantamental trading factors across various asset classes. Macrosynergy research in this field intends to show proofs of concept based on the simplest implementation of the underlying idea. For a broader set of example signals and Jupyter notebooks, please visit Examples of macro trading factors[1]. This handbook aims to illustrate the substantial value that quantamental indicators can contribute to macro trading strategies, particularly when integrated with market price information. Specifically, Chapter 5.1 The importance of macro trends, provides a summary of the theoretical justification for the significant role of macroeconomic trends in the fixed-income, equities, commodities, credit, and FX markets. Effectively utilizing these indicators requires a solid understanding of macro-quantamental data, which includes recognizing relatively infrequent but impactful trends, the significance of panel analysis across various markets, and the need to combine and transform individual indicators. To support this, the Macrosynergy academy (https://macrosynergy.com/academy) offers theoretical insights, advanced data science methodologies, and downloadable Jupyter notebooks featuring example trading factors. This chapter also presents a selection of two key posts intended to inspire further exploration of related topics: Macroeconomic cycles and asset class returns and Macro information changes as systematic trading signals.

7.1 Macroeconomic cycles and asset class returns (May 2023)

Indicators of growth and inflation cycles are plausible and successful predictors of asset class returns. For a proof of concept, we propose a single balanced "cyclical strength score" based on point-in-time quantamental indicators of excess GDP growth, labor market tightening, and excess inflation. It has clear theoretical implications for all major asset markets, as rising operating rates and consumer price pressure raise real discount factors. Empirically, the cyclical strength score has displayed significant predictive power for equity, FX, and fixed income returns, as well as relative asset class positions. The direction of relationships has been in accordance with standard economic theory. Predictive power can be explained by rational inattention. Naïve PnLs based on cyclical strength scores have each produced long-term Sharpe ratios between 0.4 and 1 with little correlation with risk benchmarks. This suggests that a single indicator of cyclical economic strength can be the basis of a diversified portfolio. This section is based on the original post Macroeconomic cycles and asset class returns[2]. The Jupyter notebook for audit and replication can be found under Jupyter notebook[3].

Defining a tradable concept of cyclical strength

Here, cyclical economic strength refers to a state in which the economy is growing at a faster pace than it could sustain in the long run. This often occurs when short-term aggregate demand exceeds the growth in productive capacity. It implies that operating rates are increasing and that, all other things equal, the prospects for labor costs and prices are shifting upward. Such cyclical strength typically calls for monetary policy tightening, as downside risks for growth and inflation are diminishing or upside risks are building.

There are other definitions of cyclical strength in economics, but this one is particularly useful for building macro trading strategies for two reasons:

– First, there is a range of economic indicators to track cyclical strength. For the below analysis, we focus on the three most popular ones:
- the estimated rate of GDP growth versus a "normal rate" ("excess GDP growth"),
- growing utilization of the labor force ("labor market tightening"),
- above-target consumer price growth ("excess inflation").

– Second, this definition of cyclical strength has clear directional implications for major asset markets. In a standard macroeconomic policy environment, growing operating rates and inflation raise real discount factors in the near term. Unexpected cyclical strengthening should reduce the value of equity and duration positions and increase the value of the local currency. Moreover, in the presence of some degree of rational inattention as summarized in Rational inattention and trading strategies[4] with respect to economic trends, cyclical strength scores should have predictive power for subsequent asset class returns.

Specifying cyclical macro-quantamental features

For a meaningful analysis of the impact of economic trends on market returns, we use indicators from JPMaQS. For this post, we use quantamental indicators to replicate the market's information state with respect to three aspects of cyclical strength:

– Excess estimated GDP growth trend: For each day this is the latest estimated GDP growth trend (% over a year ago, 3-month moving average) minus a 5-year median of that country's actual GDP growth rate. The historic median represents the growth rate that businesses and markets have grown used to. The GDP growth trend is estimated based on actual national accounts and monthly activity data, based on sets of regressions that replicate conventional charting methods in markets. View full documentation in the thematic notebook Intuitive GDP growth estimates[5]. For subsequent aggregation and analysis, we then z-score the indicator (normalize volatility) around its zero value on an expanding out-of-sample basis using all cross sections for estimating the standard deviations.

– Labor market tightening: This is a composite of three quantamental indicators that are jointly tracking the usage of the economy's labor force. The first is employment growth relative to workforce growth, where the former is measured in % over a year ago and 3-month average and the latter is an estimate based on the latest available 5 years of workforce growth. Please view documentation in the notebook Demographic trends[6]. The second sub-indicator measures changes in the unemployment rate over a year ago and over the last three months, both as a 3-month moving average Labor market dynamics[7]. The third labor market indicator is the level of the unemployment rate versus a 10-year moving median, again as a 3-month moving average. Please view Labor market tightness[8]. All three indicators are z-scored, then combined with equal weights, and then the combination is again z-scored for subsequent analysis and aggregation.

– Excess inflation: This is a composite of four different types of consumer inflation trends, namely headline and core CPI as both percent over a year ago rate and percent of the last 6 months over the previous 6 months seasonally and jump-adjusted and annualized. Full documentation in the notebook Consumer price inflation trends[9]. From all of these rates we subtract the effective inflation target of the central bank (view documentation in the notebook Inflation targets[10]) and divide by the higher of the target or 2, to make target deviations in low- and high-inflation countries comparable. As with the other cyclical strength indicator the composite has been z-scored around its zero value on an expanding out-of-sample basis.

The composite cyclical strength score is an equally weighted average of the above three z-scored aspects of that strength. Whenever not all components of the scores are available an average of the remaining z-scores is formed. Moreover, we calculate relative z-scores for each currency area, except for the U.S. and the euro area. These relative scores are needed as signals for FX-related strategies. They are calculated by subtracting from the score of the reference country the score of the currency area that is its natural benchmark, which is mostly the U.S. but for most European countries it is the euro area, and for the UK, Turkey, and Russia, it is a basket of USD and EUR.

Cyclical strength and asset class returns since 2000

Cyclical strength and equity index future returns

We can investigate the relationship between the cyclical strength of the economy and subsequent equity index futures returns for 18 developed and emerging economies' currency areas (AUD, BRL, CAD, CHF, EUR, GBP, JPY, KRW, MXN, MYR, PLN, SEK, SGD, THB, TRY, TWD, USD, ZAR) since 2000 (for currency symbols refer to Appendix 2). Generic futures return data are taken from JPMaQS and for cross-country comparability we use volatility-target versions, i.e. returns for positions that have an expected annualized 10% return volatility (view documentation Equity index future returns[11]).

On balance, mainstream economic theory suggests that cyclical strength, as opposed to sustained inflation-free growth, should be negatively related to local equity index futures returns. This is because high operating rates and inflation require tighter monetary policy and increase labor cost pressure. In conjunction with rational inattention of parts of the market, related point-in-time information should have predictive power.

Indeed, there has been a highly significant negative relation between the broad composite cyclical strength indicator and subsequent future returns across the panel (Figure 7.1). The probability of this relationship being not a chance event in the sample is more than 98% at a monthly frequency and 99% probability at a quarterly frequency based on the Macrosynergy panel test. For details on the test methodology, please view post Testing macro trading factors[12]. Similarly, Pearson and Kendall correlation coefficients of the pooled dataset have been negative, with near 100% significance.

Monthly balanced accuracy, the average ratio of correct prediction of positive and negative returns based on the (negative of) cyclical strength has been 52.3%. The cyclical strength signal's positive return predictions have been correct in 61% of all months, and its negative predictions in 44% of all months. Predictive power has been quite seasonal, with positive correlation and above 50% accuracy in 52% and 56% of all years, respectively.

Across cycle indicator components, excess inflation posted higher predictive accuracy and return correlation than excess growth and labor market tightening, but all three showed above 51% accuracy and a highly significant (negative) correlation with subsequent equity returns.

We calculate naïve PnLs based on standard rules used in all our posts:

1. Positions are taken based on cyclical strength scores in units of vol-targeted positions.
2. The z-scores are winsorized at three standard deviations to reduce the impact of data outliers.
3. Positions are rebalanced monthly with a one-day slippage for trading.
4. The long-term volatility of the PnL for positions across all currency areas has been set to 10% annualized.

It is important to note that this PnL calculation method does not consider transaction costs or realistic risk management rules.

7. Examples of macro trading factors

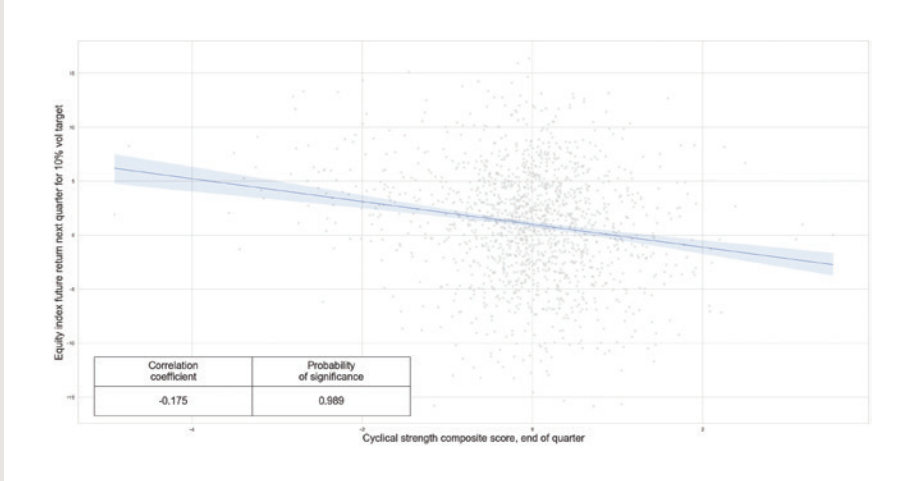


Figure 7.1: Cyclical strength and subsequent equity index futures returns, 2000-2024 (Nov)

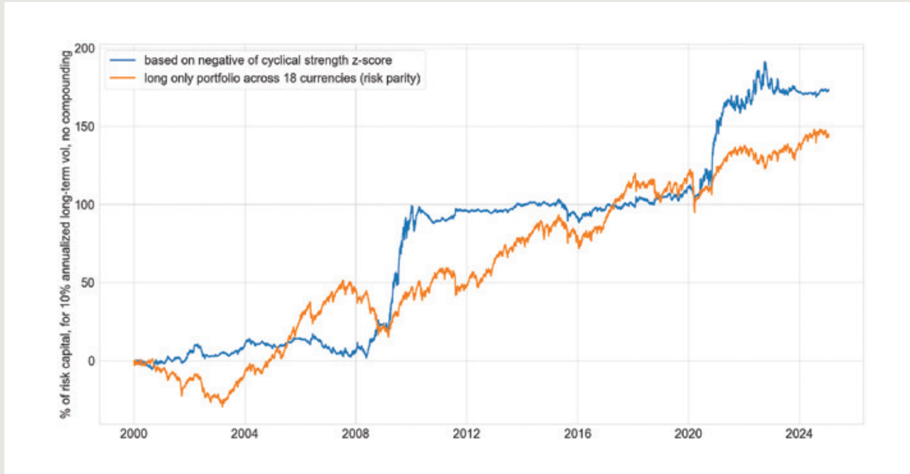


Figure 7.2: Equity index future PnL across 18 markets, 2000-2024 (Nov)

Naïve PnL generation has been positive but highly seasonal, naturally producing most value around times of recessions and recoveries (Figure 7.2). The long-term Sharpe ratio of the naïve PnL based on the cyclical strength score has been 0.7 from 2000 to 2024 (November). PnL generation has been largely uncorrelated with returns of long-only equity benchmarks (such as the S&P 500) and, hence, has been additive to standard long equity market exposure.

Cyclical strength and FX forward returns

We can investigate the relationship between the cyclical strength of the economy and subsequent 1-month FX forward returns for 27 "smaller" currency areas (AUD, BRL, CAD, CHF, CLP, COP, CZK, GBP, HUF, ILS, JPY, KRW, MXN, MYR, NOK, NZD, PEN, PHP, PLN, RON, RUB, SEK, SGD, THB, TRY, TWD, ZAR) since 2000 (for currency symbols refer to Appendix 2). FX forward returns data are taken from JPMaQS and for cross-country comparability we use (10%) volatility-target versions (view FX forward returns[13]). Periods of illiquidity or non-convertibility have been blacklisted. The exchange rates underlying the forward contracts are based on the reference currency against its "dominant benchmark", which for most cases is the U.S. dollar. However, for some European currencies, the euro is more appropriate, and for three currencies (GBP, RUB, and TRY), both the euro and the dollar serve as benchmarks.

The analysis of FX returns focuses on relative cyclical strength, which compares the cyclical strength score of the reference currency against the cyclical strength in the benchmark currency area. According to standard economic reasoning, currency areas with positive relative scores are more likely to experience relative monetary tightening and positive forward returns. Conversely, currency areas with negative relative scores are more likely to experience negative returns, all other things being equal. Since relative cyclical strength across countries is not easy to follow for investors, it is likely that there is some degree of rational inattention and that systematic relative strength scores have some predictive power.

Indeed, empirical evidence since 2000 shows a highly significant positive relation between relative cyclical strength scores and subsequent monthly or quarterly FX returns (Figure 7.3). The Macrosynergy panel test, Pearson correlation, and Kendall correlation all show a positive relation with almost 100% statistical probability that this did not occur by chance.

Monthly balanced accuracy has been 52.1%, with the ratio of correct positive return predictions at 55% and the ratio of correct negative predictions at 48%. Positive prediction results have been less seasonal than in the case of equity index futures returns, with above 50% balanced accuracy positive correlation in three-quarters of all sample years and over 80% of all currency markets. All three subcomponents of cyclical strength showed highly significant positive correlation and above 50% balanced accuracy. The labor market subcomponent posted the strongest predictive power.

The naïve PnL across all currencies from 2000 to 2004 (Nov) has been strong and positive most of the time (Figure 7.4). The long-term naïve Sharpe ratio would have been near 1 since 2000, with just a 7% correlation with the S&P500. The cyclical strength signal would have avoided some drawdowns of a long-only strategy in small countries' FX. However, it would not have avoided a drawdown during the great financial crisis of 2008.

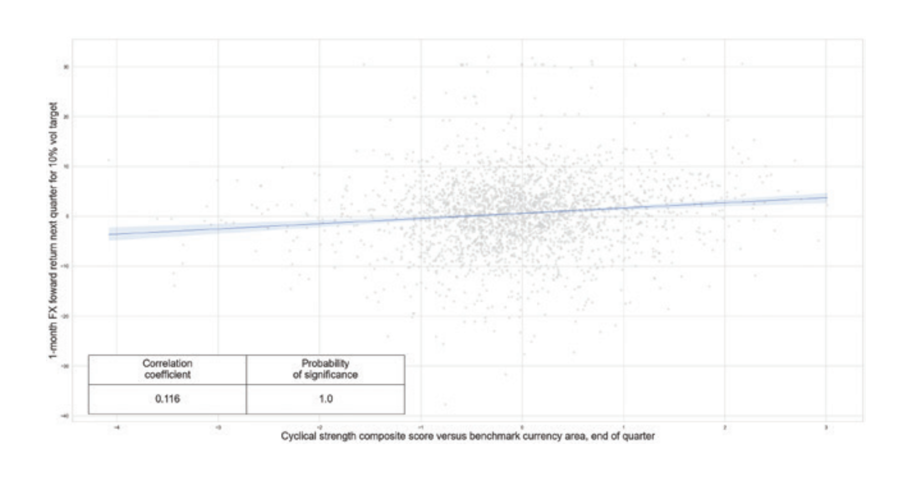


Figure 7.3: Relative cyclical strength and subsequent FX forward returns, 2000-2024 (Nov)

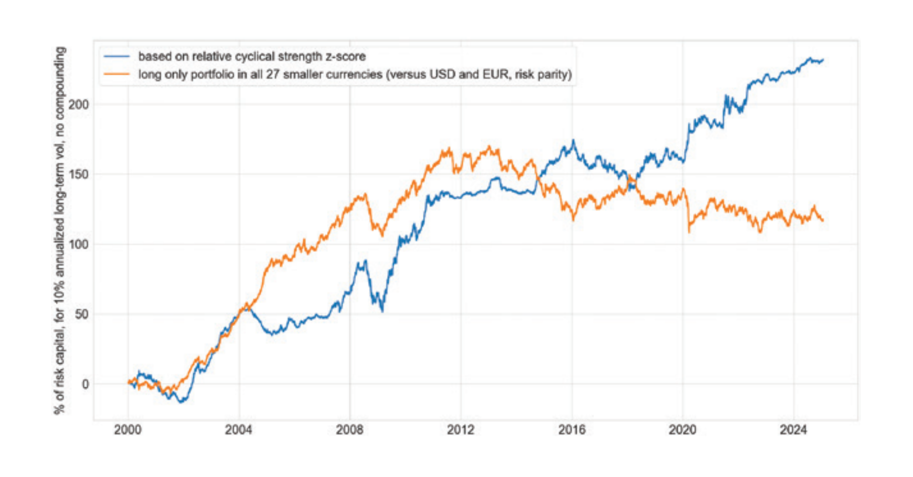


Figure 7.4: FX forward PnL across 27 currency areas (ex USD and EUR)

CONTENTS

Cyclical strength and FX versus equity returns

We can analyze the relationship between cyclical strength and relative positions in FX forwards versus local-currency equity index futures for 17 currency areas that have both liquid FX and equity futures markets (AUD, BRL, CAD, CHF, EUR, GBP, JPY, KRW, MXN, MYR, PLN, SEK, SGD, THB, TRY, TWD, ZAR) (for currency symbols refer to Appendix 2). To focus on the actual relative performance both lags of the trade are vol targeted at 10%.

The economic reasoning of the above sections applies, and we would expect cyclical strength in a currency area to favor FX performance over local-currency equity performance. Also, we test this hypothesis for both outright and relative cyclical strength indicators.

Both outright and relative cyclical strength have displayed a positive and highly significant relationship with subsequent monthly and quarterly FX versus equity returns, by all metrics (Figure 7.5). The predictive power of the relative cyclical strength signal has been slightly stronger in terms of correlation and significance, but slightly weaker in terms of directional prediction accuracy.

Monthly balanced accuracy has been 52.3% for the outright signal, and 51.3% for the relative signal. Across sub-components, the inflation and labor market scores have displayed on balance a bit higher accuracy and forward return correlation.

PnLs for both outright and relative cyclical strength signals have been economically significant, with a long-term Sharpe ratio of 0.6 and 0.8 respectively (Figure 7.6). Importantly, correlations of the naïve strategies with the broad equity market have been near zero. This differentiates them from a strategy that is always long equity versus FX. Equity typically carries higher risk premia in the spirit of the capital asset pricing theory and would have outperformed FX positions consistently over the last 10 years. However, the cyclical strength signals would also have generated a strong PnL from 2000 to 2012, when the equity long failed to perform.

Cyclical strength and interest rate swap returns

In principle, we can investigate the relation between cyclical strength and subsequent 5-year interest rate swap returns for 25 developed and emerging economies' currency areas (AUD, CAD, CHF, CLP, COP, CZK, EUR, GBP, HUF, ILS, JPY, KRW, MXN, MYR, NOK, NZD, PLN, RUB, SEK, SGD, THB, TRY, TWD, USD, ZAR) (for currency symbols refer to Appendix 2). Not all countries have been available since 2000, however, and some markets have suffered from occasional illiquidity and had to be temporarily blacklisted. Also, for some countries, cross-currency swaps have been used. Generic IRS return data are taken from JPMaQS and for cross-country comparability we use volatility-target versions, i.e. returns for positions that have an expected annualized 10% return volatility (view thematic notebook Duration returns[14]).

In principle the general hypothesis is simple: greater cyclical strength calls for higher real and nominal interest rates. In conjunction with some rational inattention in markets, a high strength score bodes for weaker or negative duration returns.

Indeed, the correlation between cyclical strength and subsequent IRS returns has been negative. However, the significance of that relationship across the panel is

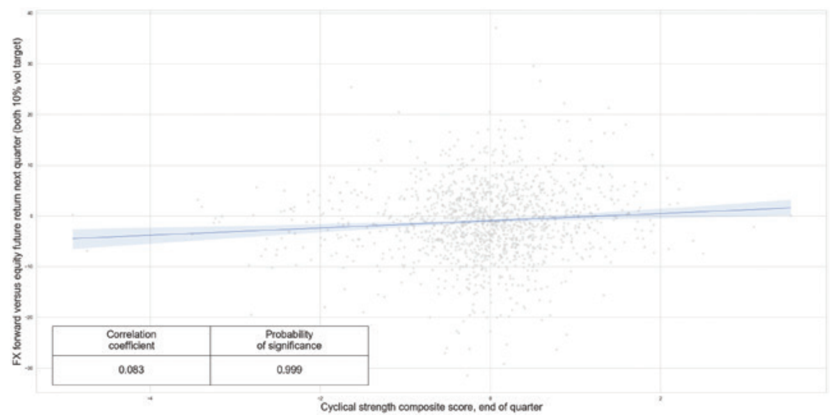


Figure 7.5: Cyclical strength and subsequent FX versus equity returns, 2000-2024 (Nov)

(a) outright signal

(b) relative signal

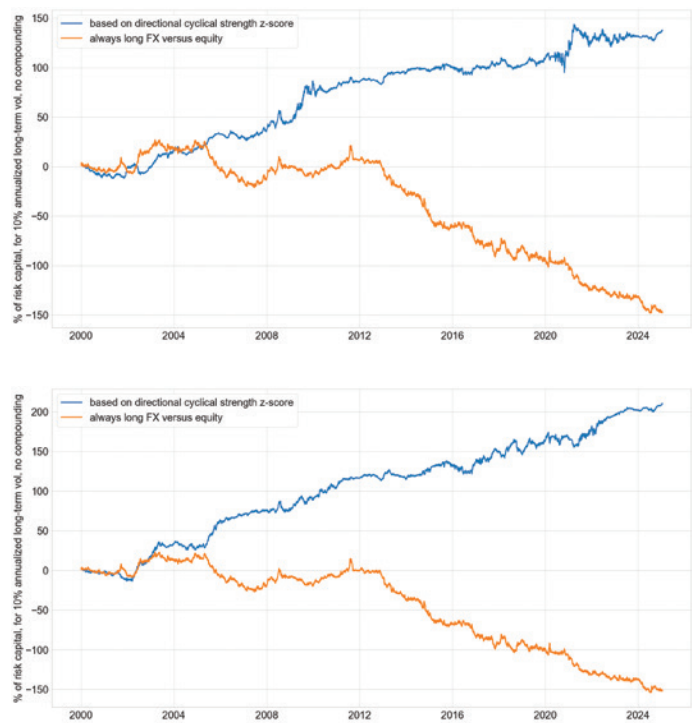


Figure 7.6: FX forward versus equity index future PnL across 17 currency areas

questionable. True, standard Pearson or Kendall correlation based on pooled data looks highly significant. However, the Macrosynergy panel test, which adjusts for pseudo-replication of observations in countries that experience similar features and target variation, assigns only 93% to the probability that the relationship did not appear by chance. This reflects the correlation of cyclical strength across economies, leading to pseudo-replication of experiences in the panel, and the strong dependence of most countries' IRS returns on developments in the U.S. and – to a lesser extent – in the euro area.

Indeed, the negative relation is clearer and stronger for the U.S. and the euro area alone, with slightly lower significance, even though it is based on a fraction of about 10% of the global data (Figure 7.7).

For the whole panel, the monthly balanced accuracy of 5-year IRS return predictions has been 52.2%, with a 58% hit ratio of positive predictions and a 47% hit ratio of negative predictions. However, predictive quality has been highly seasonal with above 50% accuracy in only 62% of all sample years and positive correlation in less than half of the years.

A long-term "naïve" PnL calculation based on the cyclical strength signal alone does not show consistent value generation (Figure 7.8). Positive returns were only accumulated since 2014, and even during this period, there was a large drawdown during the COVID pandemic. The empirical Sharpe ratio of 0.41 was only accomplished thanks to a broad global payer position of the strategy during the phase of yield increases after the pandemic.

Cyclical strength and curve flattening returns

We define a curve flattening trade as a receiver position in a 5-year interest rate swap and a payer position in a 2-year IRS, with the overall trade being volatility neutral, i.e. both legs having the same expected return standard deviation based on a standard exponential lookback window with an 11-day half-life. This is roughly equivalent to a difference of 5-year and 2-year vol-targeted IRS returns as available on JPMaQS. The sample for this analysis is the same 25 markets that were used for the directional IRS return analysis.

As long as monetary policy regimes are credible, and markets are rationally inattentive there is a strong case for cyclical strength predicting positive flattening returns and cyclical weakness negative flattening returns. That is cause monetary policy typically tightens into cyclical strength, raising near-term policy rate expectations, while controlling long-term inflation and managing a return of the economy to a steady state.

Empirically, there is strong evidence for the positive relation between cyclical strength and subsequent returns on curve-flattening positions since 2000 (Figure 7.9). Significance has been 99.5% or higher at a monthly or quarterly frequency according to the Macrosynergy panel test, the Pearson correlation of the data pool, and the Kendall correlation of the pool.

The monthly balanced accuracy of the cyclical strength composite score with respect to subsequent curve flattening returns has been 52.9%, with 56% correct positive directional predictions and 50% correct negative directional predictions. Predictive power has been quite seasonal,

7. Examples of macro trading factors

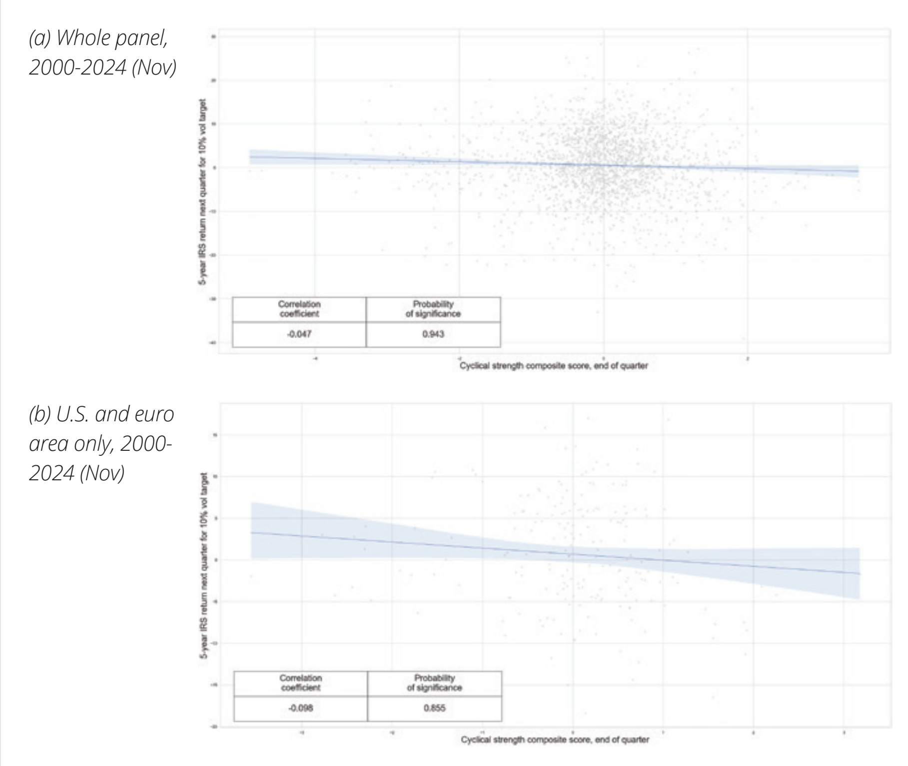


Figure 7.7: Cyclical strength and subsequent 5-year IRS returns

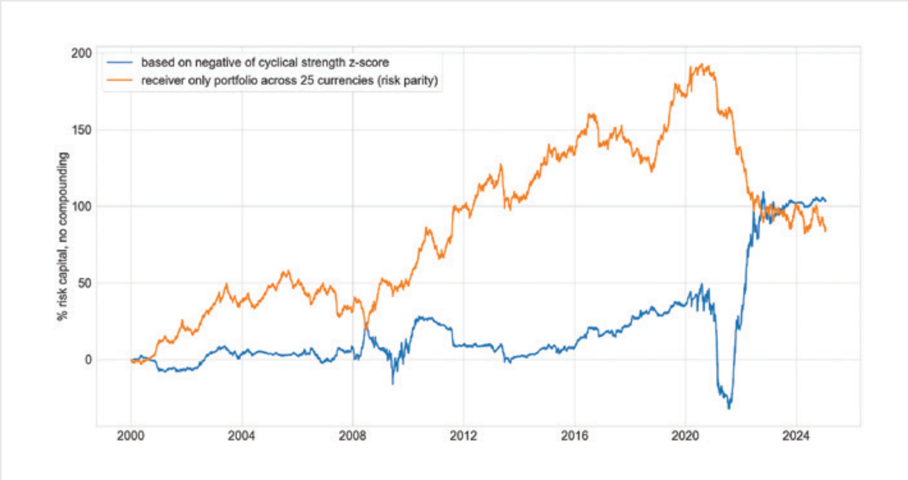


Figure 7.8: 5-year interest rate swap PnL across 25 markets

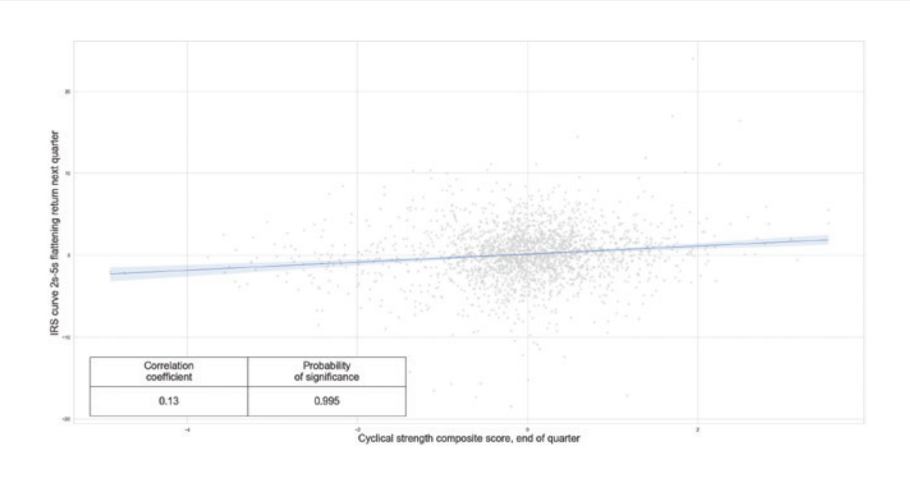


Figure 7.9: Cyclical strength and subsequent IRS flattening returns, 2000-2024 (Nov)

Figure 7.10: IRS curve flattening PnL across 25 markets

with positive correlation and above 50% accuracy in 58-66% of all sample years. All components of the cyclical strength score displayed predictive power, but the growth sub-score produced the highest correlation and balanced accuracy.

A naïve PnL with curve flattening and steepening positions based on the cyclical strength composite indicator would have produced a high long-term Sharpe ratio of 0.93 with no equity correlation and negative U.S. fixed come return correlation. However, naïve value generation was highly seasonal and concentrated in the 2020s (Figure 7.10).

Cyclical strength and FX versus IRS returns

We investigate the relation between relative cyclical strength and volatility-weighted positions in local currency FX forwards and 5-year IRS payers (short duration) across 23 currencies (AUD, CAD, CHF, CLP, COP, CZK, GBP, HUF, ILS, JPY, KRW, MXN, MYR, NOK, NZD, PLN, RUB, SEK, SGD, THB, TRY, TWD, ZAR) (for currency symbols refer to Appendix 2).

Mainstream economic theory suggests that stronger growth and inflationary pressure support local currency strength and fixed-income weakness and – in conjunction with some rational inattention – should help predict the returns on long FX versus short-duration positions.

Indeed, also this hypothesis is backed up by empirical evidence. There has been a highly significant positive relation between relative cyclical strength scores and subsequent FX versus duration returns at both the monthly and quarterly frequency. The statistical probability that this relation has not been due to chance is near 100% according to the Macrosynergy panel test, the pooled Pearson correlation p-value, and the pooled Kendall correlation p-value (Figure 7.11).

The monthly balanced accuracy of predictions based on the relative cyclical strength score has been 52.2%. Across the sub-scores the labor market tightening score posted the highest balanced accuracy. A naïve PnL of vol-targeted FX versus duration positions based on the cyclical strength score alone would have produced a respectable long-term Sharpe ratio of 0.63 since 2000 with just 5% correlation with the S&P500. The PnL has been seasonal, albeit not highly concentrated on a single episode (Figure 7.12).

7.2 Macro information changes as systematic trading signals (September 2024)

Macro information state changes are point-in-time updates of recorded economic developments. They can refer to a specific indicator or a broad development, such as growth or inflation. The broader the economic concept, the higher the frequency of changes. Information state changes are valuable trading indicators. They provide daily or weekly signals and naturally thrive in periods of underestimated escalatory economic change, adding a layer of tail risk protection. This section illustrates the application of information state changes to interest rate swap trading across developed and emerging markets, focusing on six broad macro developments: economic growth, sentiment, labor markets, inflation, and financing conditions. For trading, we introduce the concept of normalized information state changes that are comparable across economic groups and countries and, hence, can be

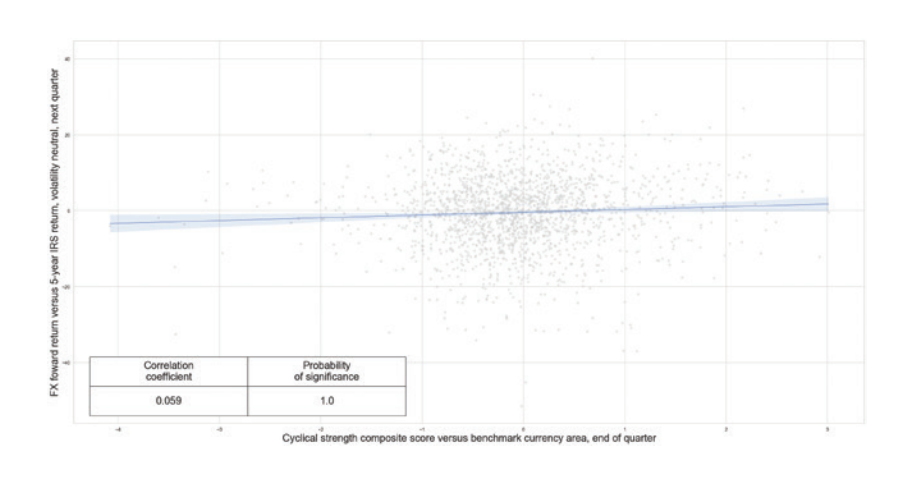


Figure 7.11: Relative cyclical strength and subsequent FX versus IRS returns, 2000-2024 (Nov)

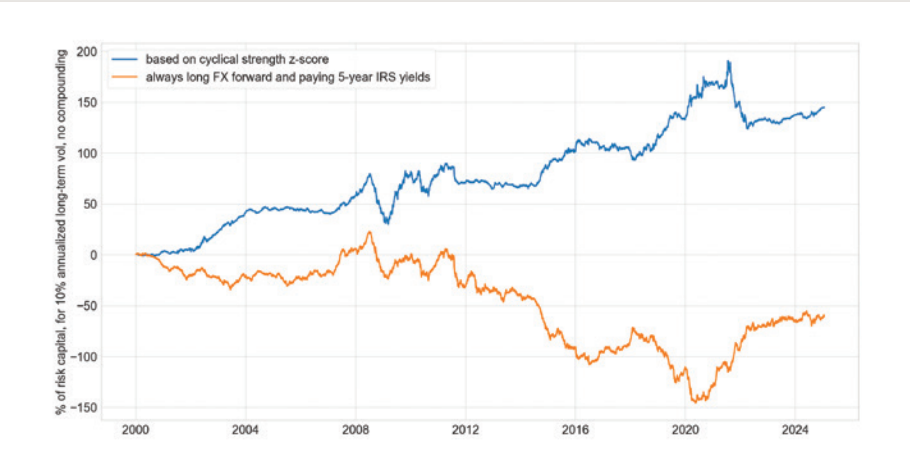


Figure 7.12: FX versus duration PnL across 23 markets

aggregated to local and global signals. The predictive power of aggregate information state changes has been strong, with material and consistent PnL generation over the past 25 years. For more information, please view Macro information changes as systematic trading signals[15] and the related Jupyter notebook[16].

The basics of macro information state changes

A macro information state is the latest instance of an economic indicator available to the public on a given date. For example, on September 18, 2024, the latest annual core CPI inflation rate of Japan was reported as 2.7% based on a change of the CPI for July 2024 versus the CPI for July 2023. The timestamp of an information state, here September 18, is different from the observation period of the economic event, here the period July 2023 to July 2024. Time series of information states represent the evolution of public records of recent economic developments. They are point-in-time data, like market prices, and unlike standard economic data. View relevant post Reported economic changes and the Treasury market: impact and payback[17].

Macro information state changes are simply the first differences of recorded information states. Conceptually, they are updates of publicly available indicators. For example, on September 19, the latest Japanese core inflation rate was updated to 2.8%, now referring to the period August 2023 to August 2024. The information state change on that date was 0.1%. Information state changes result not only from changes in observation periods but also from revisions of previously released data, changes in model parameters, such as calendar factors, or changes in reference series of an economic concept, such as the CPI data that a central bank uses to estimate core inflation.

Information state changes often refer to broad economic concepts rather than single indicators. For example, information states of broad inflation pressure in a country should consider various price indices and changes thereof. Information states of global inflation pressure should consider various metrics of price growth across a range of larger economies. The broader the concept, the more indicators become relevant and the higher the frequency of the information state changes. Information state changes in broad economic growth and inflation are almost daily.

Information state changes are not quite the same as surprises. Surprises would be information state changes that are not anticipated by the market. In practice, information state changes are partly predictable, for example, through early indicators and autocorrelation. Broad information state changes are often autocorrelated, i.e., past changes indicate future changes, as many indicators are subject to similar background trends. But predictability does not mean irrelevance. Whilst an increase in inflation may be predicted by a conscientious economist, many market participants and policymakers respond to facts rather than forecasts or prefer to save information costs. Generally, information state changes and surprises are different concepts, each relevant to markets.

The benefits of information state changes as trading signals

Information state changes are a precious type of trading signal that can be derived from point-in-time economic information:

– Higher-frequency signals: Information state changes provide higher-frequency macroeconomic trading signals than standard economic indicators. This is because information states are more variable than actual economic trends. Economic data are subject to all types of transient influences, such as unseasonal weather, holiday patterns, large-ticket transactions, and reporting changes. The disparity between actual economic change and information state changes is particularly pronounced for broad concepts. While global inflation cycles may be measured in years and decades, many specific price indicators experience idiosyncratic cycles and short-term trends or pick up relative price changes. Short-term information state changes matter even if they do not correctly predict a shift in longer-term trends because they still shape the subsequent flow of news and views expressed by market analysts. Most short-term information state changes are, with hindsight, considered noise by economists. However, for traders, they can be profitable noise.
– Macro risk protection: Occasionally, economic change is unanticipated and highly consequential. This includes periods of self-reinforcing escalating economic dynamics, such as recessions and spiraling inflation. Signals based on information state changes typically keep positions on the side of underestimated trends as they follow the change in economic information swiftly and dispassionately. This is opposite to convention in the economic profession, where analysts often "fight for their views" and adjust predictions sluggishly in accordance with publication schedules. Most information state changes may be "false dawns" whose influence on the market is small and fleeting. However, when an unanticipated change escalates, it can enforce a large-scale repricing of expectations and risk. In the below empirical analysis, fixed income signals based on information state changes did a particularly good job in periods of escalatory developments.

In the past, data on economic information states had been hard to procure and work with. However, now they can simply be downloaded from the J.P. Morgan – Macrosynergy Quantamental System (JPMaQS). JPMaQS provides daily end-of-day (New York time) information states of major macroeconomic indicators, called "quantamental indicators", for more than 50 countries and typically over 2-4 decades, based on concurrent data "vintages." For research purposes, access to these indicators (excluding the last few months of data) is free (please refer to https://macrosynergy.com/academy/academic-liaison/).

Example: relevant information state changes for rates markets

Economic growth: These are information states of indicators representing GDP growth and aggregate demand growth in the economy. They include the following quantamental categories:

– Intuitive real GDP growth[18], i.e., the latest estimable GDP growth trend based on actual national accounts and monthly activity data, based on sets of regressions that replicate conventional charting methods in markets, % over a year ago.

– Technical real GDP growth[19], i.e., the latest estimable GDP growth trend based on actual national accounts and monthly activity data based on supervised learning and standard nowcasting: % over a year ago.
– Industrial production[20], adjusted for seasonal effects, working days and holidays: % of the latest 3 months over the previous 3 months at an annualized rate.
– Real private consumption[21], % over a year ago, 3-month average or quarterly.
– Real retail sales[22], % over a year ago, monthly or quarterly frequency.
– Merchandise imports[23] in local currency, seasonally adjusted, % of the latest 6 months over the previous 6 months at an annualized rate, monthly frequency.

Economic sentiment: These include information states of survey-based confidence scores of various areas of the economy, namely of the following categories:
– Manufacturing business confidence[24], seasonally adjusted normalized (z-)score.
– Services business confidence[25], seasonally adjusted normalized (z-)score.
– Construction business confidence[26], seasonally adjusted normalized (z-)score.
– Consumer confidence[27], seasonally adjusted normalized (z-)score.

Labor market: This looks at information states with respect to unemployment rates and employment growth rates:
– Unemployment rate[28], seasonally adjusted, 3-month moving average.
– Employment growth[29], main local measure, % over a year ago, monthly or quarterly frequency.

Inflation: These are information states of various consumer and producer price growth rates that market participants and central banks conventionally monitor:
– Headline CPI inflation[30], % over a year ago, including early estimates where available.
– Core CPI inflation[31], % over a year ago, local standards, including early estimates where available.
– Producer price inflation[32], % over a year ago, local standards.

Financing: The final group contains information states of credit and liquidity growth rates as approximations of ease of financing:
– Private credit growth[33], change over 12 months ago, as % of GDP, seasonally and jump-adjusted.
– Narrow money[34], seasonally- and jump-adjusted, % change over a year ago.
– Broad money[35], seasonally- and jump-adjusted, % change over a year ago.
– Net international investment position[36], as % of GDP.
– International liabilities[37], as % of GDP.

The currency areas for which these series are gathered are nine developed markets and 13 emerging markets. The developed market currency areas are (in alphabetical order if the currency symbol): Australia (AUD), Canada (CAD), Switzerland (CHF), the euro area (EUR), the United Kingdom (GBP), Japan (JPY), Norway (NOK), New Zealand (NZD), Sweden (SEK), and the United States (USD). The emerging markets are Chile (CLP), Colombia (COP), Czechia (CZK), Hungary (HUF), (ILS), India (INR), South Korea (KRW), Mexico (MXN), Poland (PLN), Thailand (THB), Turkey (TRY), Taiwan (TWD), and South Africa (ZAR). Periods of illiquidity, such as the early 2000s in some emerging markets and Turkey after 2020, have been excluded.

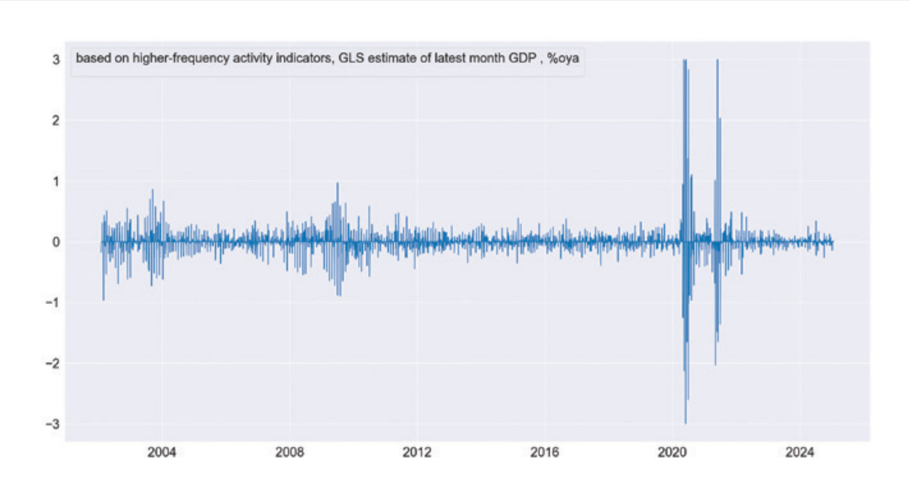


Figure 7.13: Example: U.S. GDP growth nowcast, normalized information state changes, inverted

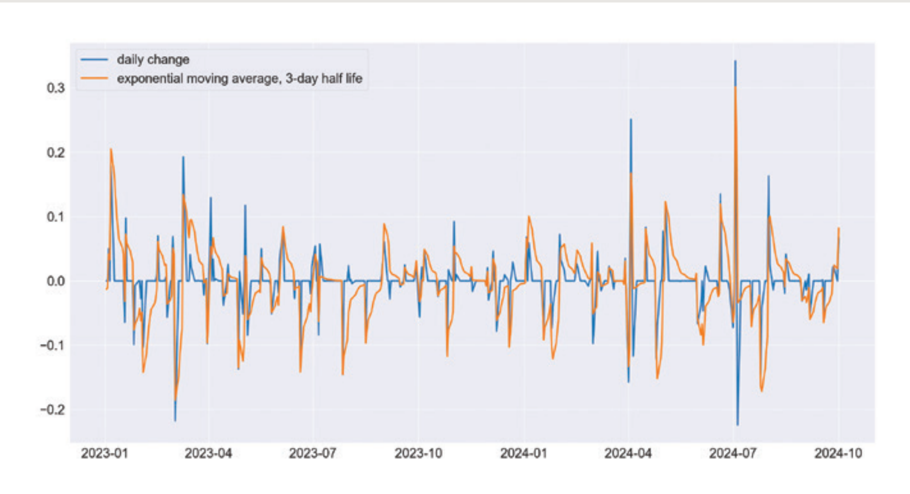


Figure 7.14: U.S. GDP growth nowcast 2023/24: normalized information state changes, inverted

Standardizing information state changes

Generally, we define information state changes for specific economic indicators as normalized daily changes in units of standard annualized changes of that indicator. The purpose of normalization is to make information state changes comparable across different indicators and units, thus allowing aggregation. For regular time series, normalization would just mean division by daily standard deviations. However, the daily variance of information states is extremely uneven across time. Variation is typically high on the first release dates for an observation period, much lower on revision dates, and zero on all other days. To have a common interpretable basis for normalization, we only consider the standard deviation of new observation period releases as the denominator.

Furthermore, we need to "annualize" the changes to make high and low-frequency economic reports comparable. The change of a quarterly report conveys more information than the change of a weekly report, as more time has passed. Hence, we divide by the square root of the number of observation periods in the year, assuming that those changes are roughly approximated by an unbiased discrete random walk. We call the output of these transformations normalized information state changes in annualized units (NICA). Typically, these normalized metrics are winsorized to de-emphasize extreme outliers.

Note that in this section, all information state changes are plotted and applied with the sign of their expected impact on duration positions. Thus, for inflation and growth changes, a negative sign is applied. The chart (Figure 7.13) shows normalized information state changes for a U.S. GDP nowcast that is based on a range of activity indicators. This time series looks very different than standard economic indicators related to growth, with volatility dominating trends most of the time.

Aggregation of information states

The value proposition of information state changes as a trading signal relies on the principle of rational information inefficiency, i.e., the choice of investors not to follow and act on each potentially relevant new data release in real-time (view The macro information inefficiency of financial markets[38]). Rather, many investors limit themselves to reviewing economic changes on a periodic basis, maybe weekly, relying on aggregation across economic data and countries, often filtered by economist briefings and news reports. Of course, there are some key data that are widely received in real-time, such as the U.S. labor market report. However, the full range of relevant economic data changes is too vast for a human investor to analyze in real-time and even challenging to follow periodically.

Therefore, this post proposes to model and predict gradual information updates based on standardized information state changes. This typically requires various types of aggregation.

Temporal aggregation: It is plausible that new information permeates the markets over a couple of days. An efficient version of that process can be modeled through exponential moving averages of past normalized information state changes. We have chosen a half-life of 3 days and separately tested 5 days, with similar results. Broadly speaking, this assumes that information is being mostly absorbed over the course of a week or two, which corresponds with the frequency of many research reports and briefings (Figure 7.14).

Cross-indicator aggregation: What matters for market perception is not so much the change of a single indicator as a change in a broad trend or state, such as economic growth or inflation. For example, if a range of indicators related to aggregate demand and output all show an acceleration, the message has greater publicity and credibility and, hence, probably greater impact. Here, we aggregate by forming linear averages of normalized information state changes across all indicators that belong, respectively, the groups of economic growth, economic sentiment, labor market, inflation and financial conditions. The averages are unweighted for simplicity, but weights could also be set based on judgment of data importance or optimized through statistical learning (Figure 7.15).

Cross-group aggregation: To arrive at a single plausible diversified trading signal, one can aggregate conceptual group averages of normalized information state changes as a form of "conceptual parity". This is possible through linear combination because the scales of group values are comparable, and their signs are all set such the positive values are presumed to have a positive effect on duration returns. As for cross-indicator aggregation, this post uses unweighted averages, but optimized weightings based on past explanatory power and statistical learning would be an option (view methodological post Regression-based macro trading signals[39] and Figure 7.16).

Global aggregation: Finally, country-specific information state change metrics can be aggregated into global measures. This is appropriate for directional trading across connected markets and economies, where trends in one country matter for others. Again, a linear combination is suitable as an approximation. However, given the different sizes of economies and their financial markets, plausible weights must be applied. For this post, we used point-in-time values of the shares of local GDP in world GDP in USD terms, based on a 3-year moving average (view Global production shares[40] and Figure 7.17).

Aggregation naturally increases autocorrelation of information state change indicator. Temporal aggregation introduces serial relations mathematically. Cross-indicator, cross-group, and cross-country aggregation effectively combine related economic phenomena, and to the extent that common background factors drive them, they often change in the same direction. Still, as long as the initial temporal aggregation uses short horizons, aggregate information state changes are still short-term signals by the standards of economic factors, as they typically change direction every few days.

The PnL value of aggregate information state changes

We test the predictive power and economic value of aggregate information state changes for the overall economy and various conceptual groups. This follows a general evaluation method that considers the seasonality and diversity of macro trading signals across countries Evaluating macro trading signals in three simple steps[41].

The facet of scatterplots and regression lines in Figure 7.18 visualizes and quantifies the relation between information state changes at the end of a week and the subsequent weekly duration returns across the full panel of 22 countries for the near 25-year period 2000 – 2024

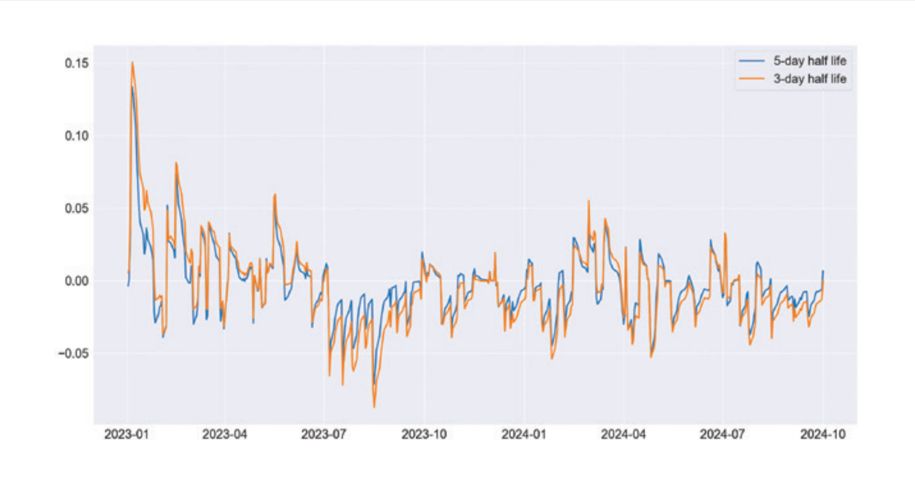


Figure 7.15: U.S. broad output and demand-growth-related normalized information state changes, 2023/24, inverted

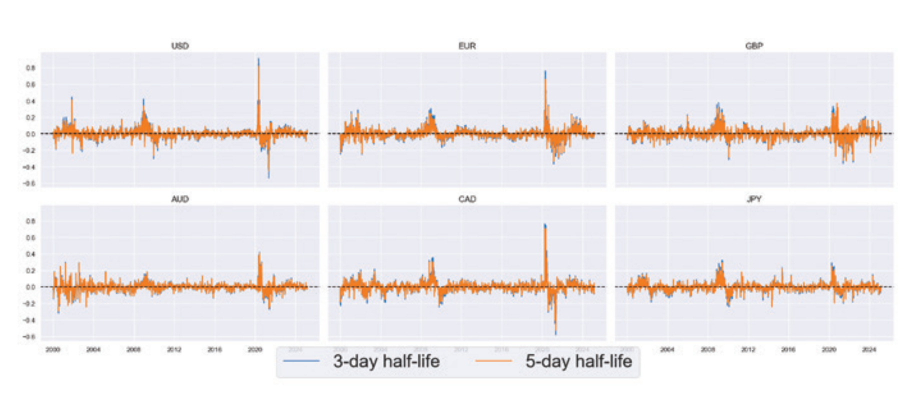


Figure 7.16: Composite macroeconomic information state changes for duration risk, selected currencies, average across groups

CONTENTS

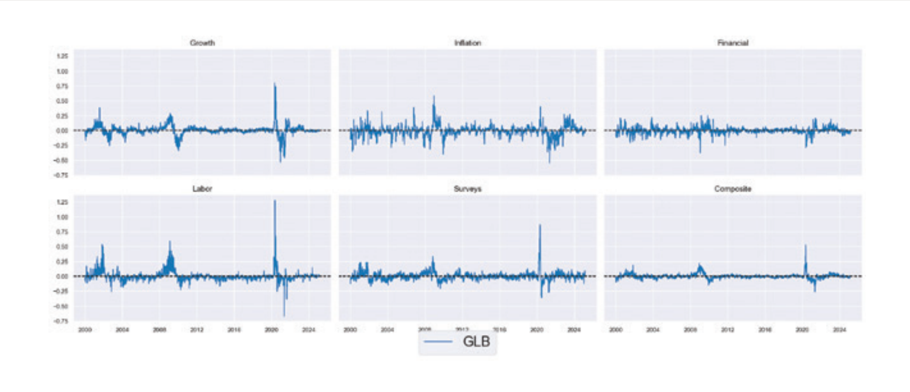


Figure 7.17: Global information state changes for duration risk, GDP-weighted average across countries

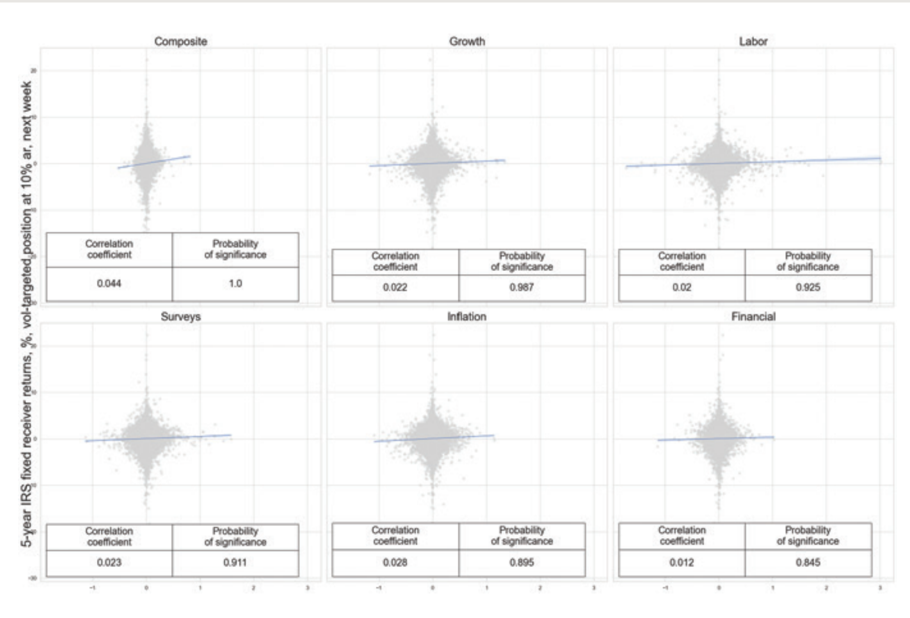


Figure 7.18: Macroeconomic information state changes and subsequent weekly duration returns, 22 countries, since 2000

(September). The critical metric is the significance of the weekly forward correlation, which is based on a special panel test that adjusts the data of the predictive regression for common global influences across countries view (Testing macro trading factors[42]). This test assumes that the relation between features and targets are similar across most countries and that the country-specific features matter, not just their global averages.

The panel regression analysis shows the positive predictive power of aggregate short-term information state changes for all conceptual economic groups and the aggregate. The changes related to composite and economic growth have been most significant, with probabilities of non-accidental relationships of over 99%. The probability of significance in the other four groups has been between 85% and 93% (Figure 7.18). Beyond, the predictive power of the composite information state change has also been highly significant at a daily or monthly frequency.

The daily accuracy of information state changes with respect to the next day's returns has been above 50%. Also, the parametric and non-parametric forward correlation has been positive and highly significant for all macro groups except financial conditions.

Finally, we can measure the economic value of the information state changes as trading signals based on naïve PnL metrics. Naïve profit and loss series can be calculated by taking positions in the form of one unit of expected volatility per unit of normalized signal. Positions are adjusted daily, using the previous day's information state change values and adding one day of slippage of trading into the new position. The trading signals are capped at a maximum of two standard deviations as a reasonable risk limit. The naïve PnL does not consider transaction costs or risk management rules. It will thus overstate the economic return for large amounts of assets under management but gives an objective evaluation of the signal value itself. We consider a market-neutral strategy and a long-biased strategy, whereby the latter always adds one standard deviation of the information state change signal. All PnLs are scaled (not volatility targeted) to 10 annualized standard deviations for joint graphical representation.

The 25-year risk-adjusted return of a strategy based on the composite information state changes across 22 currency areas has been material. The long-term Sharpe ratio of the naïve PnL has been 1.4 with near zero correlation to the 10-year Treasury return and without counting compounding effects. The Sortino ratio has been as high as 2.2. Seasonality has been modest for a macro signal, with consistent value generation across decades and only the 2009-10 episode of sustained negative PnLs. The PnL contribution of the 5% best-performing months has been less than 50%. Meanwhile, the information state changes provided particularly high value in times of escalating economic change, such as around the great financial crisis or the COVID-19 pandemic and the subsequent reflation period.

A long-biased strategy would still have produced a 25-year Sharpe ratio of over 1, compared to a Sharpe ratio of 0.4 for a simple long-only risk-parity exposure across all 22 markets. Thus, the information state change has also proven its value as a cross-market and intertemporal risk allocation overlay signal (Figure 7.19).

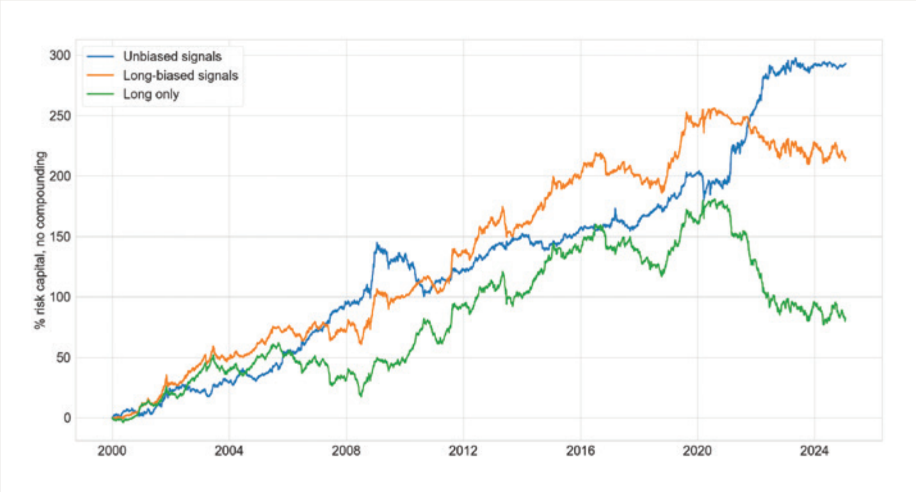


Figure 7.19: Naive PnLs of IRS positions based on local and global macro information changes (22 countries)

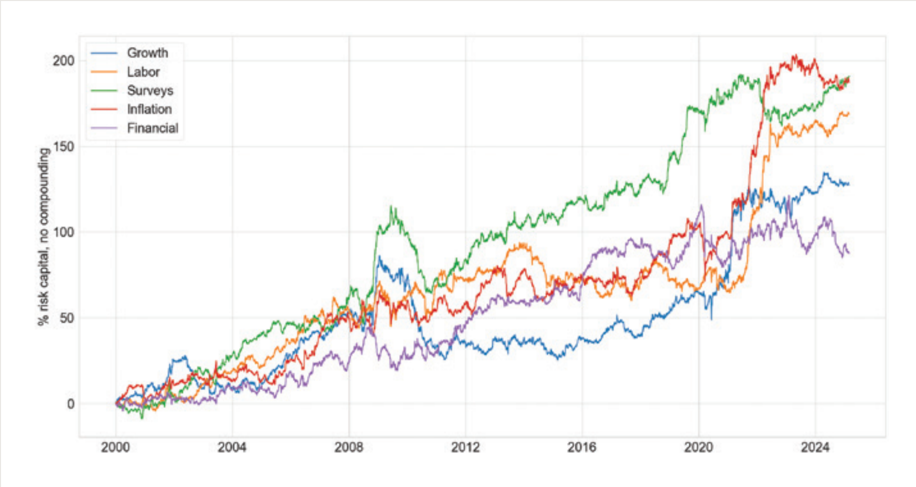
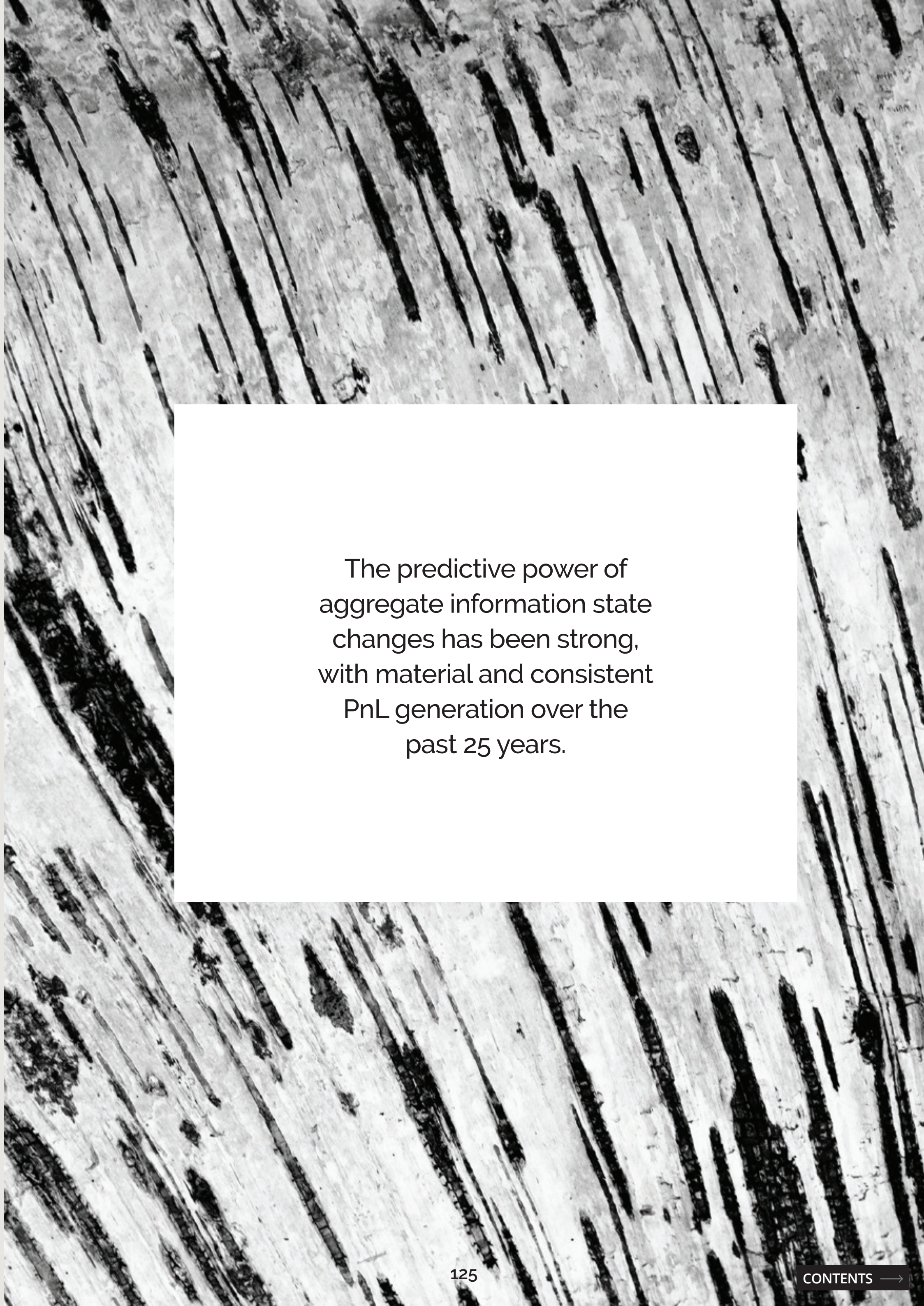


Figure 7.20: Naive PnLs of global IRS positions based on macro group information state changes (unbiased signals)



The predictive power of aggregate information state changes has been strong, with material and consistent PnL generation over the past 25 years.

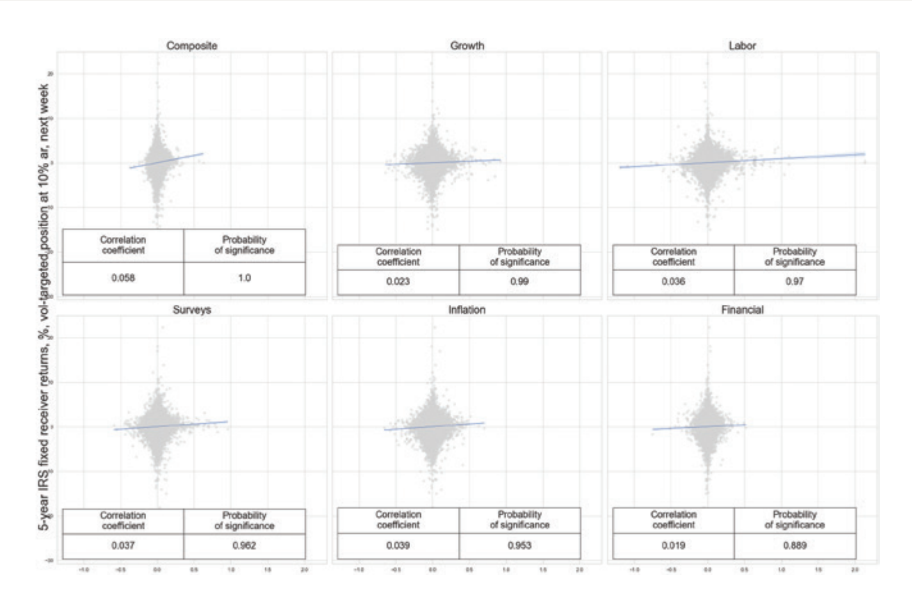


Figure 7.21: Global/local macro information changes and subsequent weekly duration returns, 22 countries, since 2000)

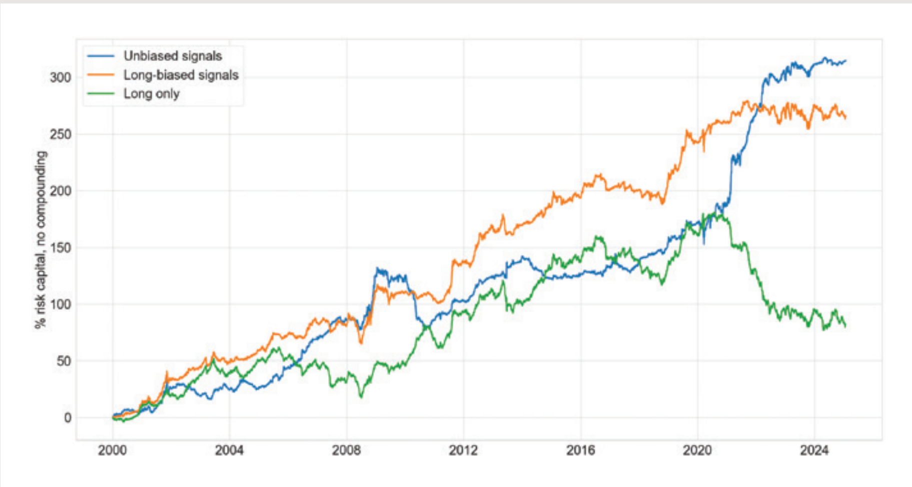


Figure 7.22: Naive PnLs of IRS positions based on local and global macro information changes (22 countries)

Naïve PnL generation has also been positive for all individual economic groups' information state changes. Each of them would have added significant value. This testifies to the broad and pervasive predictive power of macro information changes. The most "profitable" field of information state changes has been inflation, albeit sentiment-based signals have delivered greater consistency. In general, the seasonality of individual economic concepts has been greater than for the composite signals, highlighting the benefits of diversification. Different economic trends matter in different periods. The only exception has been survey changes, which have generated PnL values almost linearly across time (Figure 7.20).

An alternative to country-specific signals is combined local-global information state changes. Rather than just considering the information on the local economy, these signals consider local and global changes equally. In practice, participants in local fixed-income markets follow international developments. Those in smaller economies often pay more attention to U.S. or euro area data than to their own economic reports.

Indeed, the predictive power of combined local and global information state changes has reached even greater significance than local information alone. All macro group changes have displayed a weekly forward correlation with a probability of significance of at least 93%. Also, the daily accuracy of return predictions has been higher than for local signals alone (Figure 7.21).

Considering both local and global information state changes has produced slightly better risk-adjusted returns in naïve PnLs without greatly changing the overall return profile. The 25-year Sharpe ratio of the unbiased signals would have been 1.5, and the Sortino ratio 2.5. The Sharpe ratio for the long-biased signal would have been 1.3, and its Sortino ratio 1.9 (Figure 7.22).

7.3 Overview of the macro trading factors

The Macrosynergy academy lists 35 trading ideas[43] (as of December 2024) across all asset classes. Here is the list of all existing posts (most of them are accompanied by relevant downloadable Jupyter notebooks):

Category	Title and links
Cross asset class	– Equity versus fixed income: the predictive power of bank surveys[44] – Macroeconomic cycles and asset class returns[45] – Excess inflation and asset class returns[46] – Intervention liquidity[47] – Macro factors of the risk-parity trade[48]
Equity factors	– Cross-country equity futures strategies[49] – Statistical learning for sectoral equity allocation[50] – Macro factors and sectoral equity allocation[51] – Macro trends and equity allocation: a brief introduction[52] – Equity trend following and macro headwinds[53] – Inflation and equity markets[54] – Equity market timing: the value of consumption data[55] – Job growth as trading signal[56]
Fixed income factors	– Macro information changes as systematic trading signals[57] – Macro demand-based rates strategies[58] – Merchandise import as predictor of duration returns[59] – Fiscal policy criteria for fixed-income allocation[60] – The predictive power of real government bond yields[61] – Trend following: combining market and macro information[62] – The power of macro trends in rates markets[63] – Inflation expectations and interest rate swap returns[64] – Duration volatility risk premia[65]
Foreign exchange	– Advanced FX carry strategies with valuation adjustment[66] – FX trading signals with regression-based learning[67] – FX trading signals: Common sense and machine learning[68] – FX trend following and macro headwinds[69] – Pure macro FX strategies: the benefits of double diversification[70] – Modified and balanced FX carry[71] – How to use FX carry in trading strategies[72] – Economic growth and FX forward returns[73]
Commodity factors	– Inventory scores and metal futures returns[74] – Business sentiment and commodity future returns[75] – Commodity carry as a trading signal – part 1[76] – Commodity carry as a trading signal – part 2[77] – Predicting base metal futures returns with economic data[78]
Credit Factors	– Sovereign debt sustainability and CDS returns[79]

8 Data science and macro trading factors

Statistical learning offers methods to extract insights from datasets, leveraging the increasing availability of quantitative data. It supports estimating relationships between variables (parameters) and selecting models for such estimates (hyperparameters). For macro trading, statistical learning provides another key advantage: realistic backtesting. By simulating rational, rules-based choices of models and features, it avoids decisions that are dominated by hindsight and recent experiences. However, data on macroeconomic developments and their impact on modern financial markets are limited. This is due to the relatively short history of derivatives markets and the rarity of critical macroeconomic events, such as business cycles, policy changes, and financial crises. For instance, the U.S. has experienced only four business cycles and one major financial crisis since 1990, according to the NBER. While datasets like the J.P. Morgan Macrosynergy Quantamental System (JPMaQS) provide valuable daily-frequency information spanning decades, dominant macro developments remain infrequent and valuable for research. Python libraries, such as scikit-learn, have made statistical learning easy. Combined with the Macrosynergy package[1], these tools enable the creation of machine learning solutions for macro-quantamental indicators. This chapter includes two specific use cases: FX trading signals with regression-based learning[2] and Statistical learning for sectoral equity allocation[3]. The full collection of machine learning use cases can be found under Statistical methods with quantamental indicators[4].

8.1 FX trading signals with regression-based learning (April 2024)

Regression-based statistical learning helps build trading signals from multiple candidate constituents. The method optimizes models and hyperparameters sequentially and produces point-in-time signals for backtesting and live trading. This post applies regression-based learning to macro trading factors for developed market FX trading, using a novel cross-validation method for expanding panel data. Sequentially optimized models consider nine theoretically valid macro trend indicators to predict FX forward returns. The learning process has delivered significant predictors of returns and consistent positive PnL generation for over 20 years. The most important macro-FX signals, in the long run, have been relative labor market trends, manufacturing business sentiment changes, relative inflation expectations, and terms of trade dynamics. View original post FX trading signals with regression-based learning[5] and the Jupyter notebook[6].

The case for regression-based learning

Regression-based learning can be used to combine candidate constituents (or features) into single signals for trading strategies. The method chooses models and hyperparameters sequentially and produces related point-in-time signals that are suitable for realistic backtesting and directly applicable to live trading. The basics of the method have been introduced in the post Regression-based macro trading signals[7].

Regression-based learning is particularly useful if one wishes to consider a broad set of conceptually different and potentially complementary signal constituent candidates. This is often the case for macroeconomics-based trading strategies, as the state of the economy and monetary policy is dependent on a range of relevant forces.

The benefits of the regression-based approach are convenience and simplicity. Regression-based learning automatically assigns weights to the signal constituent candidate scores based on past statistical relation and – for some regression methods, such as non-negative least squares and elastic net – removes candidates that have insufficient or implausible explanatory power. Meanwhile, the linear form of the standard regression models and the familiar interpretation of its coefficients allow simple inspection of the learning process, enhancing transparency.

Plausible macro trading indicators for FX

The focus of this post is on macro trading signals for directional FX forward positions in seven "smaller" developed countries versus their natural benchmarks. In particular, we aim at predicting returns in 1-month FX forward positions in all developed markets' currencies, excluding the G3 (U.S, euro area, and Japan):

– the Australian dollar (AUD), the Canadian dollar (CAD), and the New Zealand dollar (NZD) are all versus the U.S. dollar (USD);
– the Swiss franc (CHF), the Norwegian krone (NOK), and the Swedish krona (SEK) are all versus the euro; and
– the British pound (GBP) is versus an equally-weighted basket of U.S. dollar and euro.

For the analysis below, we focus on volatility-targeted 1-month FX forward positions, which are rolled and rebalanced at a monthly frequency. For more details on the generic return calculation, view thematic notebook FX forward returns[8].

There is a broad range of candidate economic data that are plausibly related to the performance of developed market currencies, measuring the competitiveness of the economy, the attractiveness for capital flows, and the outlook for monetary policy. The main argument for the predictive power of such information with respect to future returns is the economic theory of rational inattention, which argues that market participants are unable to continuously process all relevant information and – rationally – set priorities, simplifying the world into a small set of indicators. The theory has been explained in the post Rational inattention and trading strategies[9]. Economic trends and states are too numerous to track in real-time and are typically less carefully monitored than market price and flow data.

To ascertain the predictive power of recorded economic developments, we need point-in-time data on information states of the market. They are available from the J.P. Morgan Macrosynergy Quantamental System (JPMaQS). This data service provides macro-quantamental indicators, i.e., macroeconomic information states designed for the development and backtesting of trading strategies. An information state is the latest instance of an economic indicator based on the data vintage available on a given day. This type of indicator is conceptually free from all look-ahead bias. In JPMaQS, quantamental indicators are usually produced in similar form for a broad range of countries. These panels are called quantamental categories.

For the foreign exchange space, JPMaQS contains a particularly wide array of quantamental categories. In fact, there are too many to consider in a single post. Therefore, here we focus on a reduced set of quantamental categories that correspond to data and news that are commonly watched in discretionary currency trading:

– Relative excess GDP growth trends: Conceptually, this is the difference between current estimated GDP growth trends in the local currency area and the benchmark currency area. Generally, a positive growth differential versus the benchmark currency area supports positive returns on the local currency, as it is indicative of greater competitiveness and tighter monetary policy. The basis of the indicator is the JPMaQS category group "intuitive GDP growth estimates," real-time estimated recent GDP growth trends (% over a year ago, 3-month average) based on regressions that use the latest available national accounts data and monthly-frequency activity data. The indicator mimics common methods of market economists. View Intuitive GDP growth estimates[10].

– Manufacturing confidence changes: These are changes in normalized headline measures of local-currency area manufacturing business sentiment. Generally, improving confidence in tradable goods industries signals stronger competitiveness and is a leading indicator of better news flow. The basis of the indicator is the JPMaQS category group "manufacturing confidence scores," real-time standardized and seasonally adjusted measures of manufacturing business confidence and their changes based on one or more surveys per country and currency area. For the full documentation view Manufacturing confidence scores[11]. For the analysis, we consider an average of 3-month-over-3-month changes and 6-month-over-6-month changes in survey scores.

– **Relative unemployment trends:** These are recent changes in seasonally adjusted unemployment rates in the local economy versus the benchmark currency area. Relative tightening of the labor market in the local currency area bodes for relative tightening of monetary policy. The basis of the indicator is the JPMaQS category group "labor market dynamics," which contains real-time measures of changes in employment and unemployment. View the thematic notebook Labor market dynamics[12]. Here, we use an average of 3-month-over-3-month, 6-month-over-6-month, and over a year ago changes in seasonally adjusted unemployment rates.

– **Relative excess core CPI inflation:** Conceptually, this indicator measures the excess of local core inflation versus the excess of core inflation in the benchmark currency area. Excess here means relative to the central bank's inflation target. If local inflation exceeds its target more than in the benchmark currency area, it is more likely that the local central bank will run a tighter monetary policy and tolerate currency strength. The basis of the indicator calculation is the JPMaQS categories Consistent core CPI trends[13] and Inflation targets[14]. Specifically, we use an average of 3-month-over-3-month, 6-month-over-6-month, and over a year ago annualized changes in core CPI and subtract from this the currency area's effective inflation target.

– **Relative excess GDP deflators:** This is the difference between the broad excess GDP deflator trend in the local economy and the benchmark currency area. Excess means relative to the inflation target. Higher local currency area excess deflator growth indicates both pressures for tighter monetary policy and improving terms of trade. GDP deflator trends are part of the JPMaQS category group "Producer price inflation." Within that group are indicators of estimated economy-wide output price growth based on standard econometric ("technical") estimates that use GDP deflators as targets but are nowcast based on higher-frequency price information. View thematic notebook Producer price inflation[15]. Here, we estimate the economy-wide estimated output price growth as % over a year ago in 3-month moving averages.

– **Relative inflation expectations:** This is the difference between estimated inflation expectations in the local economy and the benchmark currency area. Higher relative inflation expectations across similar economies typically translate into tighter monetary policy and greater tolerance for currency strength. Here, inflation expectations refer to formulaic estimates of the JPMaQS category group "Inflation expectations (Macrosynergy method)[16]." Here, we use an average of 1-year, 2-year, and 5-year inflation expectations.

– **Relative real interest rates:** This is the difference between the real short-term interest rate in the local market and in the benchmark currency area. Higher real interest rates are indicative of higher implied central bank subsidies (or lower penalties) and higher risk premia. The real short-term rates are taken from the JPMaQS category "Real interest rates". In particular, we use the main 1-month money market rate adjusted for formulaic inflation expectations. View Real interest rates[17].

– **International liability trends:** Conceptually, these are changes in recorded external financial liabilities of residents to non-residents over the medium term. A rapid increase in liabilities indicates large past capital inflows that may be hard to sustain and, hence, increases the risk of subsequent currency weakness. The basis of the indicator calculation is international liabilities as % of GDP from the JPMaQS category group "International investment position." View thematic notebook International investment position[18]. Here, we look at trends in information states of liabilities versus the past two years and five years in percentage points of GDP and take an average.

– **Terms-of-trade dynamics:** These are changes in export prices relative to changes in import prices. Improving terms of trade often precede economic outperformance, capital inflows, and positive economic news, all of which support currency strength. The basis of terms-of-trade dynamics here is the commodity-based terms-of-trade dynamics of the JPMaQS group "Terms-of-trade." Commodity-based terms of trade use commodity trade and price data alone and can be consistently updated in real-time at a daily frequency (view Terms-of-trade[19]).

The above categories have been chosen and calculated based on theoretical priors, not statistical optimization. For convenience, all constituent candidates are given the "right sign" that makes their theoretically expected predictive direction positive. Moreover, all signal constituent candidates are sequentially normalized around their zero value, i.e., each indicator is divided by the standard deviation of a panel of the indicator in the past, avoiding a look-ahead bias. We call the normalized data signal constituent candidate scores.

Correlation across the candidate scores has been modest for most pairs (Figure 8.1) but with notable exceptions, such as the correlation of relative inflation expectations and relative core CPI inflation (positive) and of relative real interest rates and relative inflation expectations (negative). This illustrates that even if signal constituent candidate scores are conceptually different and, hence, separation is valid, statistical correlations can large both on the negative and positive side. Regression-based learning naturally takes the correlation of features into account. This approach is valid if we believe that past statistical relations are a good guide for the future.

A simple regression-based learning approach

To combine the nine candidate scores we use a simple sequential regression-based statistical learning process. Starting history with a minimum sample (of 3 years for two cross sections), we determine at the end of each month an optimal regression model from a grid of variations through cross-validation. Then, a signal is derived for the next month as the regression-based forecast using the concurrently optimal model version. This means signals vary over time not only because economic indicators change but also because model versions and parameters change. The sequence of the optimized signal is a valid basis for the out-of-sample final evaluation of the overall learning process, based on statistical criteria and a naïve stylized cumulative profit and loss time series (PnL).

CONTENTS ⟶

In practical terms, this approach can be implemented in the following steps, as exemplified in the accompanying Jupyter notebook[20].

– **Transform features and targets into suitable formats for scikit-learn:** It is important to remember that the features and targets of the analysis are panel data, i.e., two-dimensional datasets that contain one category across time and relevant countries of currency areas. These data are transformed into a (pandas) data frame for all features (X) and a double-indexed series of targets (y). The index dimensions are cross-section (currency area) and time. Periodicity is downsampled, here from daily to monthly, by using the latest value of the features and the sum of the targets. Finally, the features are lagged by one period.
– **Define appropriate cross-validation splitters:** Cross-validation methods for panels have been summarized in the post Optimizing macro trading signals – A practical introduction[21]. Here, we use the training data splitting of the RollingKFoldPanelSplit[22] class, which instantiates splitters of temporally adjacent panel training sets that can border the test set from the past and future. An illustration of this method is shown in Figure 8.2.

We implement a novel version of this splitter here, which sets the number of splits in accordance with the overall length of the panel. This means that in sequential optimization, the number of splits used in cross-validation increases over time. This illustrates an important feature of regression-based learning: under structural stability of relations, the quality of statistical learning increases with the expanding dataset (view Figure 8.3).

– **Define an appropriate score for cross-validation:** Here, we simply choose the conventional R2 metric to compare model versions in cross-validation.
– **Definition of candidate models and hyperparameters:** These are collected in two Python dictionaries of regression models and their hyperparameter grids. These can then be passed on to the appropriate scikit-learn classes and methods or their Macrosynergy package wrappers. The specific grids used are described below.
– **Run sequential model optimization and signal generation:** This uses the SignalOptimizer[23] class of the learning module of the Macrosynergy package. It mainly serves as a wrapper of standard scikit-learn cross-validation that respects the panel structure of the underlying data.

Finally, the optimized signals are evaluated using standard evaluation functions of the Macrosynergy package. For details and replication, view the related Jupyter notebook[24].

As benchmarks for signal evaluation, we used both a "long-only" portfolio of small country FX forwards, i.e., risk parity longs in the small countries' currency versus the U.S. dollar and the euro, and a conceptual parity strategy. The conceptual parity signal simply averages all signal constituent candidate sores. This requires no estimation, but if the set of candidates is chosen with good judgment, conceptual parity is typically a high benchmark. Unlike statistical learning, which relies on theoretical

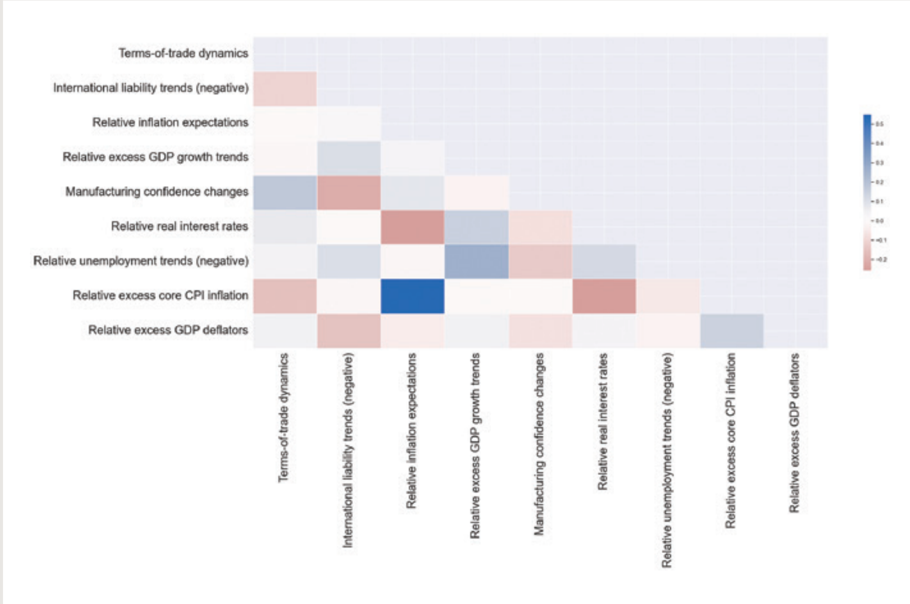


Figure 8.1: Monthly cross-correlation of signal constituent candidates for a panel of seven developed market countries since 2000

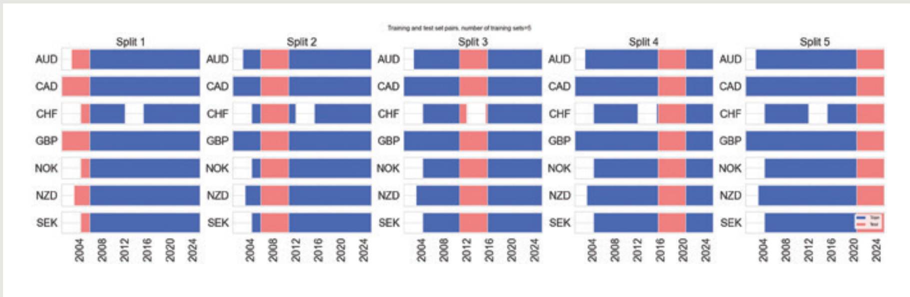


Figure 8.2: Training and test set pairs, number of training sets = 5

CONTENTS

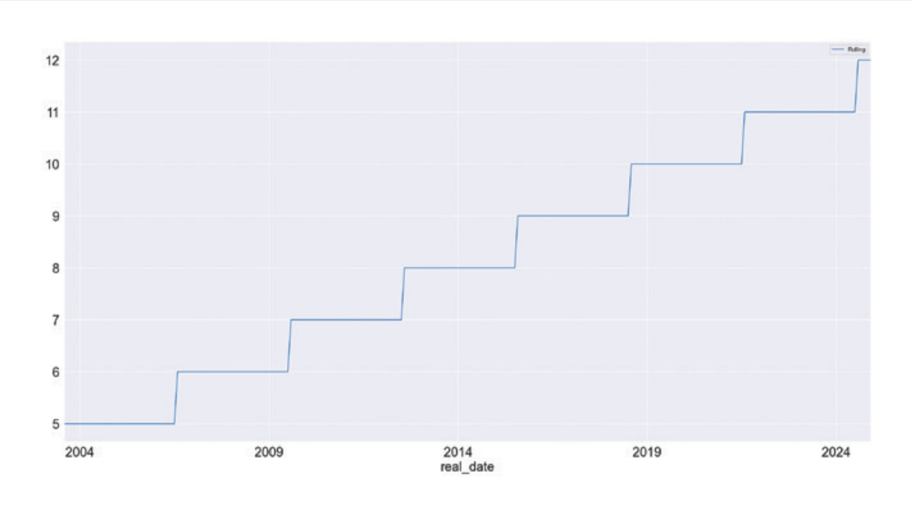


Figure 8.3: Number of splits used for rolling k-fold cross validation

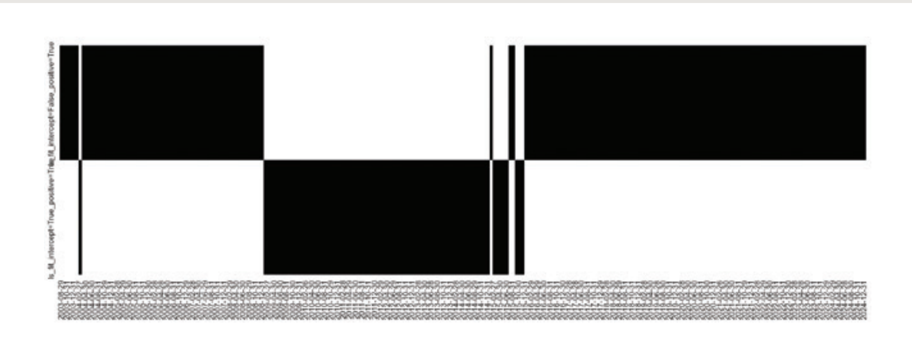


Figure 8.4: Selected least-squares models over time, based on cross-validation and R2

plausibility, it is widely diversified, and the only source of signal variation is the underlying data, not changes in model parameters or hyperparameters.

Empirical findings of simple least-squares regression learning

For a simple ordinary least squares (OLS) learning process, the small model and hyperparameter grid consider linear regression with two hyperparameter decisions:

– **Inclusion of a regression intercept:** Conceptually, the neutral level of all (mostly relative) signal constituent candidates is zero. Hence, the regression intercept is presumed to be zero, albeit that may not always be exact, and some theoretical assumptions may have been wrong.
– **Non-negativity constraint:** This offers the option of non-negative least squares (NNLS) rather than simple OLS. NNLS imposes the constraint that the coefficients must be non-negative. This restriction benefits by allowing for the consideration of theoretical priors on the direction of impact, reducing dependence on scarce data.

Inspection of the learning process shows that over time, the preferred model becomes the most restrictive one (Figure 8.4). Since 2016, regression without intercept and non-negative constraint has been chosen. This tendency has been shown in previous case studies and reflects the frequently poor biasvariance trade-off in macro trading models: model flexibility reduces potential misspecification comes at a high price of enhanced variance, i.e., sample-based variation of models and forecasts.

The bar chart 8.5 shows the influence of various constituent scores on signal prediction over time. To be precise, the colored bar sections refer to the average annual regression coefficients of all signal constituent candidate scores considered. Since the scores are normalized, the coefficients are valid measures of the importance of the constituents. While coefficients fluctuated a lot in the early parts of the sample, they stabilized in the 2010s.

Over the past ten years, four conceptual candidates dominated the signal:

– relative unemployment trends,
– manufacturing confidence changes,
– relative inflation expectations, and
– terms-of-trade dynamics.

This does not mean other signal constituent candidate scores should be disregarded going forward. The influence of different macro trends can come with long seasonality. For example, relative real interest rates and the dynamics of international liabilities played important roles during the times of the great global FX carry trade and the great financial crisis before losing statistical power thereafter. Two other observations are important:

– First, coefficients can be quite changeable and large in size in short samples since specific events and trends heavily influence them.
– Second, the size of coefficients decreased over time. Individual constituent coefficients may find it harder to fit longer samples with diverse experiences than episodes of only a few years. Since regression-based signals typically only consider prediction value size, not statistical quality, there is a danger that the declining coefficients will result in an unwanted decline in signals over time.

Compared to conceptual parity, OLS learning-based signals posted greater fluctuations in the early parts of the sample periods. Overtime variability diminished and converged for many countries, which is another indication of a “declining signal” problem (Figure 8.6).

Panel-based regression confirms the significant positive predictive power of the OLS learning-based signals with respect to subsequent weekly, monthly, and quarterly FX returns. The Macrosynergy panel test[25] assigns above 95% probability of a non-accidental relation for all frequencies (Figure 8.7).

Monthly accuracy and balanced accuracy, i.e., the average correct prediction of positive and negative returns, have been near 54%. Both Pearson and Kendall (non-parametric) forward correlation has been significantly positive and higher than for the conceptual parity signal.

As for other use cases of quantamental trading signals, we calculate naïve PnLs. These are based on monthly position rebalancing in accordance with the optimized signals for all seven currencies, normalized and winsorized at the end of each month. The end-of-month score is the basis for the positions of the next month under the assumption of a 1-day slippage for trading. The naïve PnL does not consider transaction costs, risk management, or compounding. In Figure 8.8, the PnL has been scaled to an annualized volatility of 10%.

The long-term naïve Sharpe ratio of the learning-based strategy from September 2003 to April 2024 has been above 0.5, and the Sortino ratio near 0.8. These two performance ratios have been slightly better than those of the conceptual parity strategy. Moreover, the value generation of the learning-based has been more consistent over time. Unlike conceptual parity, the learning-based PnL continued drifting up in the 2020s. Moreover, the correlation of the learning-based PnL to the S&P500 and the 10-year U.S. treasury bond has been near zero.

The learning-based signal’s performance characteristics are encouraging (Figure 8.8). One should consider that the strategy only has seven markets to trade in, some of which are highly correlated. Also, the strategy only uses macro signals without considering market prices and volumes. Position changes are infrequent and gentle.

However, the naïve PnL of the regression-based learning signal also illustrates a flaw of this simple process. As regression coefficients of optimal OLS models declined over time, so did the absolute values of the signals. As a result, PnL generation flattened, even though the quality of the signal increased over time. This suggests that the simple regression-based prediction, without consideration of statistical power and significance of the underlying model coefficients, is insufficient as a determinant of position sizes.

Other regression-based learning processes

Beyond simple OLS regression-based learning, we consider three other types of regression-based learning processes. Principally, these processes are similar to the one described above, except that they use different models and hyperparameter grids:

– Regularized regression-based learning: Regularization aims at reducing the generalization error of regression models by adding penalties in accordance with the size of the

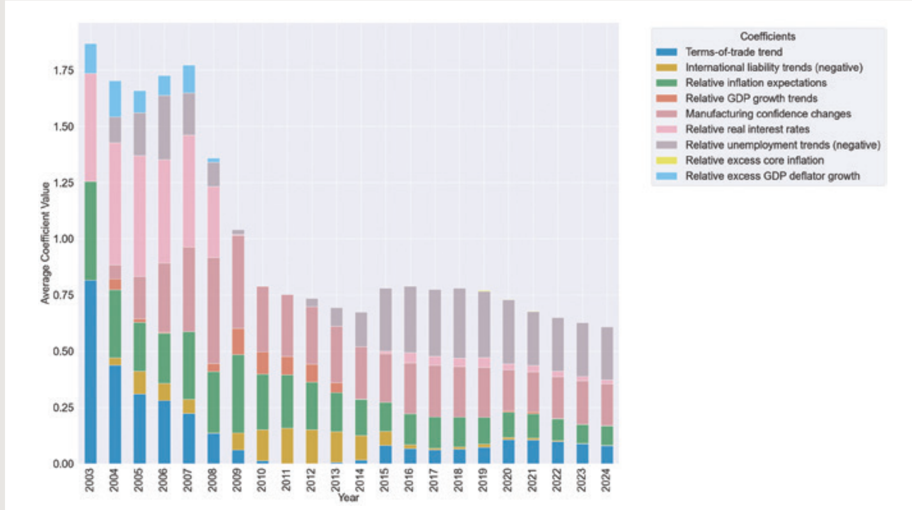


Figure 8.5: Optimal models’ average regression coefficients for normalized features

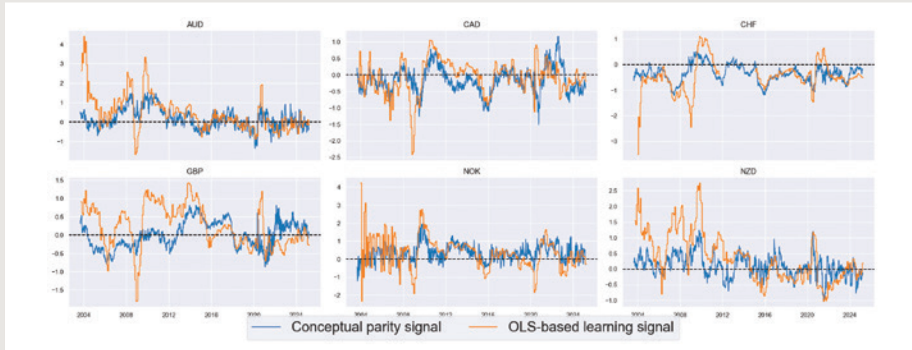


Figure 8.6: Developed market FX forward trading signals (6 selected): conceptual parity versus OLS-based learning

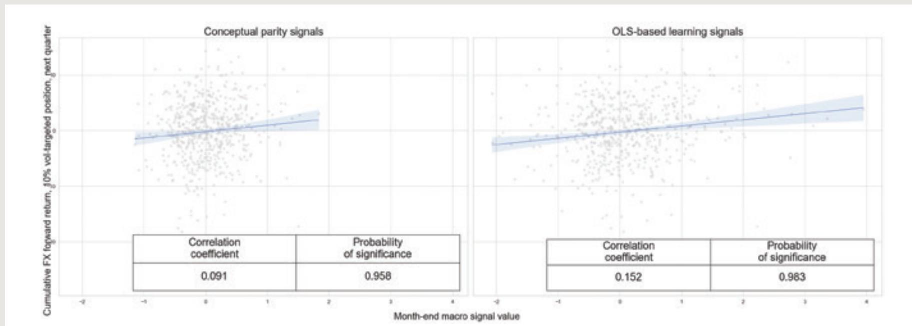


Figure 8.7: Macro signals and subsequent quarterly cumulative FX returns, 2003-2024

CONTENTS

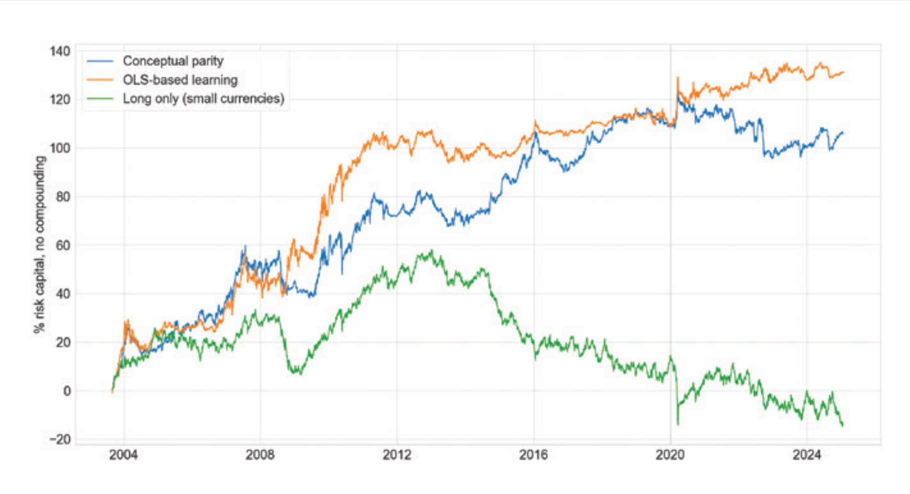


Figure 8.8: Developed market FX forward trading signals: conceptual parity versus OLS based learning

Figure 8.9: Developed market FX forward trading signals: various regression-based learning methods

coefficients. This can mitigate overfitting. Here the learning algorithm chooses from a range of elastic net regressions with varying emphasis on L1 versus L2 regularization and different penalties for coefficient size, as well as simple OLS regression. Both elastic net and OLS can have intercept exclusion and non-negative constraints.

– **Sign-weighted regression-based learning:** Sign-weighted least squares equalize the contribution of positive and negative target samples to the model fit. The learning process can choose between sign weighted and ordinary least squares, both with intercept exclusion and non-negativity constraints.

– **Time-weighted regression-based learning:** Time-weighted least squares allow prioritizing more recent information in the model fit by defining a half-life of exponential decay in units of the native dataset frequency. The learning process can choose between time-weighted and ordinary least squares, with the former choosing among half-lives of exponential lookback windows between 12 and 240 months.

All learning processes have produced signals with a positive correlation with subsequent monthly or quarterly returns. Also, most of the relationships have been significant, with over 90% probability. The only exception has been learning based on regularized regressions, which posted below 90% significance values for monthly and weekly frequency.

Accuracy and balanced accuracy values at a monthly frequency have been in a range of 53-55% for learning-based signals, a bit higher than for conceptual parity (below 52%). Also, Kendall's monthly forward correlation coefficients have been highly significant for all learning processes.

Naïve PnLs have mostly been positive, with consistent value generation. Sign-weighted learning and time-weighted learning have produced similar performance metrics as simple OLS-based learning, with Sharpe ratios between 0.5 and 0.6 and Sortino ratios between 0.7 and 0.8. The correlation of PnLs with bond and equity benchmarks has been marginal. The elastic net process underperformed (Figure 8.9).

The underperformance of elastic net methods may not be accidental. Shrinkage-based regularization reduces model coefficients, making them less sensitive to specific data samples. The idea is that introducing some bias into the regression can help reduce the variance in predictions made. Whilst theoretically sound, this, in practice, leads to more frequent model changes, as the appropriate type and size of penalties must be estimated based on the scarce data. This accentuates a source of signal variation that is unrelated to macro trends.

8.2 Statistical learning for sectoral equity allocation (September 2024)

There is sound reason and evidence for the predictive power of macro indicators for relative sectoral equity returns. However, the relations between economic information and equity sector performance can be complex. Considering the broad range of available point-in-time macro-categories that are now available, statistical learning has become a compelling method for discovering macro predictors and supporting prudent and realistic backtests of related strategies.

This research shows a simple five-step method to use statistical learning to select and combine macro predictors from a broad set of categories for the 11 major equity sectors in 12 developed countries. The learning process produces signals based on changing models and factors per the statistical evidence. These signals have been positive predictors for relative returns of all sectors versus a broad basket. Combined into a single strategy, these signals create material and uncorrelated investor value through sectoral allocation alone. For more information please view post Statistical learning for sectoral equity allocation[26], Jupyter notebook 1[27], and Jupyter notebook 2[28].

The basic idea

Macroeconomic point-in-time indicators can predict the relative performance of equity sector returns (view Macro trends and equity allocation: a brief introduction[29] and Macro factors and sectoral equity allocation[30]). This reflects that earnings and risk premia across sectors differ in their sensitivities to macroeconomic conditions, such as the state of business cycles, relative price trends, and inflation. Moreover, the absence of published articles on the relation between macroeconomic variables and sector equity returns suggests that this area of research is underdeveloped and that equity markets are far from efficient in using macro information.

In a recent post, we tested the predictive power of pre-selected plausible macro factors for the relative performance of 11 major equity sectors in 12 developed countries over an almost 25-year period since 2000 (view post Macro factors and sectoral equity allocation[31]). The finding was that conceptual risk parity signals, i.e., simple averages of normalized factors, displayed significant predictive power and applied to simple naïve strategies, sizable investor value. However, a challenge in finding macro factors for equity returns is the lack of clear theoretical guidance and the complexity of relations between macroeconomic trends and sectoral corporate balance sheets. This may erode confidence in theoretically and empirically valid factors ("fear of false positive") and cause investors to overlook the value of less obvious but relevant factors ("prevalence of false negative").

A valid path to mitigating these problems is statistical learning. The basic idea is that rather than preselecting a set of plausible macro factors for each sector's outperformance, we merely select a large range of macro factors that could conceivably exercise predictive power. Then, a learning process is applied sequentially, each month selecting the best prediction method and most relevant macro predictors for each sector's relative returns. After selecting predictors, various types of regression are considered for aggregating the selected factors into a single sectoral signal. The most successful selection-prediction method based on history to that date is then chosen to make a prediction. There are two major benefits of this learning process:

– Prudent backtests: The peril of ad-hoc predictor pre-selection is a hindsight bias. Theoretical hypotheses often develop based on a practitioner's historical experience or – worse – are derived by data mining. The learning backtests fully ignore such knowledge. They may be unnecessarily ignorant in the early years of the backtested sample. However, they invite less upside bias and moral hazard, which are typically greater threats to success in live trading.

– Discovery of hidden or subtle factors: Sectoral balance sheets and economic dependencies are very information-intensive, and even researchers with the best domain knowledge may overlook relations. Statistical learning has a better chance of eventually discovering less obvious relations.

The drawback of the method is its waiver of reasonable priors and theory and, hence, the greater risk that temporary episodes dominate predictions, even if the environment has changed. This is particularly important in the macro space, where certain conditions can be prevalent for years or even decades. Thus, in macro-trading practice, the reliance on statistical learning involves a bias-variance trade-off. Statistical learning reduces bias by considering a wide array of factors beyond the scope of personal judgment and conventional wisdom but also increases variance, as predictions are more dependent on past experiences than general theory or long-term structural propositions.

The data

Equity sector return data

The strategy targets of this post are cash equity excess returns for the 11 standard sectors of the "Global Industry Classification Standards" or GICS: Energy (ENG), materials (MAT), industrials (IND), consumer discretionary (COD), consumer staples (COS), health care (HLC), financials (FIN), information technology (ITE), communication services (CSR), utilities (UTL), and real estate (REL). For a brief characterization of each of these sectors, refer to Appendix 3.

Sectoral cash equity return data have been imported from JPMaQS for 12 economies (view Sectoral equity index returns[32]), which are (alphabetically by currency symbol): Australia (AUD), Canada (CAD), Switzerland (CHF), the euro area (EUR), the UK (GBP), Israel (ILS), Japan (JPY), Norway (NOK), New Zealand (NZD), Sweden (SEK), Singapore (SGD), and the U.S. (USD). The underlying equity return data comes from the J.P. Morgan SIFT database. SIFT stands for Strategic Indices Fundamental Toolkit. The focus of the below research is on relative volatility-targeted cash equity returns. Relative here means sector return minus the return of the equally weighted basket of all 11 sectors. The volatility-targeted returns are returned on a cash position in an index that is scaled to a 10% volatility target based on the historical standard deviation for an exponential moving average with a half-life of 11 days. Positions are rebalanced at the end of each month.

Macro predictor data

Macro predictors or factors here are macro-quantamental indicators, i.e., states and trends of the economy in a point-in-time format. These are available from the J.P. Morgan Macrosynergy Quantamental System (JPMaQS). Unlike regular economic time series, their values are based solely on information available at the time of record, i.e., original or estimated data vintages. Therefore, macro-quantamental indicators can be compared to market price data and are well-suited for backtesting trading ideas and implementing algorithmic strategies.

We consider a broad range of 56 quantamental categories, i.e., indicators

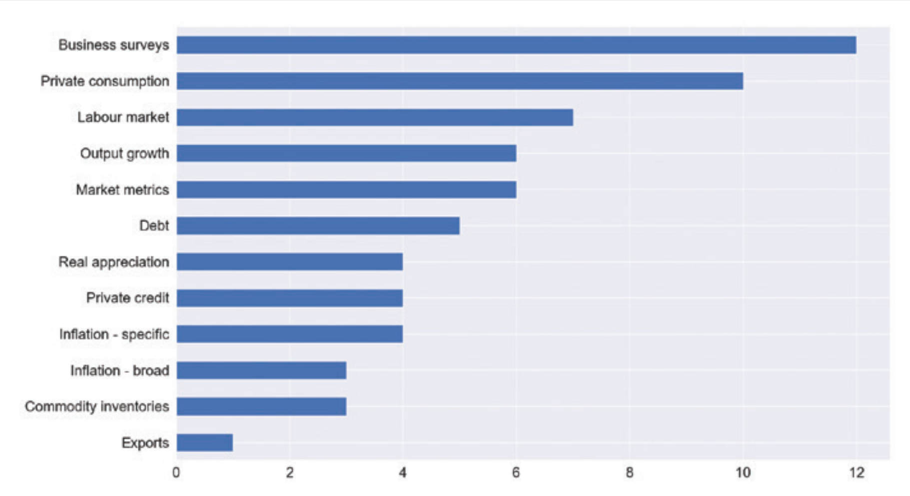


Figure 8.10: Number of categories by aggregate macro group

that are available for all 12 economies or as a global influence. The quantamental categories can be roughly divided into 12 groups: excess output growth, excess private consumption and retail sales growth, excess export growth, labor market indicators, business survey scores, excess private credit growth, excess broad inflation, excess specific (food and energy CPI inflation), debt and debt servicing ratios, commodity inventory scores, openness–adjusted real appreciation and commodity-based terms of trade, and interest rate and market metrics. This selection is the same as that used for Macro factors and sectoral equity allocation[33]. It has been left unchanged for consistency and is not exhaustive (Figure 8.10). Principally, the whole content of JPMaQS would be eligible for factor candidates, but this would make the operation of the related notebook more time-consuming.

Appendix 4 summarizes all macro-quantamental categories considered. They come in three geographical flavors. Local categories, such as economic growth, are specific to each of the 12 economies. Global categories, such as commodity inventories, are single communal indicators that are used to predict sectoral equity returns in all countries. Finally, weighted categories are weighted averages of local and global values, whereby international weights are set in accordance with the share of external trade flows to GDP. Which one is appropriate depends on the nature of the sector and macro category. For example, the impact of real interest rates on banks is mostly local, but the impact of industry growth on manufacturers is typically a combination of local and global conditions.

The application of statistical learning

The detection and application of macro factors with statistical learning follows the basics developed in previous posts (view Optimizing macro trading signals – A practical introduction[34] and Regression-based macro trading signals[35]) and proceeds in five steps:

1. We prepare suitable panel data sets for statistical learning pipelines with scikit-learn, weeding out categories with insufficient data and imputing missing data sets in individual cross sections.
2. We define a small range of feature selection methods and feature combination methods for the statistical learning process.
3. We define suitable cross-validation splitters and performance criteria for the cross-validation of the statistical learning process.
4. We operate specialized Python functions based on scikit-learn that manage sequential monthly model selection and signal generation.
5. We test the predictive power and economic value of the learning-based signals through standard procedures used in Macrosynergy posts.

Category exclusions and cross-sectional imputations

This step mainly deals with quantamental categories that have insufficient data, i.e., that are not available for most cross sections or have a short history. A standard statistical learning process requires all feature candidates to be available for a country and date to generate a signal. Even a single missing category out of over 50 principally translates into a missing signal. There are two ways to prevent missing data from escalating the loss of historic signal generation:

– **Exclusion** means that we remove categories that fail criteria on available cross-sections or history. Here, we require categories to be available for at least ten countries (at some point over the sample period) and have a history from 2003.
– **Imputation** means that under certain conditions, we fill in missing values for an individual cross sections and date with the average indicator value of the available cross sections for that date. At least 40% of the cross-sections must have valid data on any given date for the remaining to be imputed. Also, imputation is disallowed for some categories that are purely idiosyncratic and for which global averages are not meaningful estimates, namely real effective exchange rates and terms of trade changes.

For further analysis, we also needed to blacklist certain sectors for periods during which they were not tradable. This is typically the case when a smaller country does not have companies representing the sector. This is accomplished by using so-called blacklist dummies that can be downloaded from JPMaQS (please view notebook Sectoral equity index returns[36]).

Setting up feature selection and prediction methods

Statistical learning uses scikit-learn functions and specialized wrappers for macro-quantamental data panels. The learning models or pipelines all have two parts: a **"selector"** that chooses the predictors that deliver the best explanatory power and a **"predictor"** that delivers regression-based return forecasts based on a combination of chosen predictors.

– The **selector** method is Least Angle Regression (LARS), an algorithm suitable for high-dimensional data, i.e., datasets with a high number of predictor candidates relative to available observations. LARS operates a particular type of forward stepwise regression. At the outset, the coefficients of all predictor candidates are set to zero. Then it moves the coefficient of the most correlated predictor towards its least-squares value while also considering other variables. LARS changes direction toward the new predictor when another predictor becomes equally correlated with the residuals. This continues until the desired number of predictors with non-zero coefficients has been reached. For this purpose, the implementation of LARS uses the LarsSelector class[37] of the Macrosynergy package to select categories based on panel regressions. It considers the historic predictive power of predictor panels on target panels rather than just for individual cross-sections. A category needs to have predictive power across the full set of 12 economies or countries to be selected. The learning process decides the optimal number of categories that shall be selected.

– The **predictor** methods are regression types that can be used to combine different quantamental categories into single trading signals. Here, we consider simple linear regression, sign-weighted least squares, and time-weighted least squares. Sign-weighted least squares (SWLS) equalize the contribution of positive and negative samples to the model fit. Time-weighted least squares (TWLS) allow prioritizing more recent information in the model fit by defining a half-life of exponential decay in units of the native dataset frequency. The usage of these methods in the context of statistical learning and their relative strengths and weaknesses have been explained in methodological post Regression-based macro trading signals[38]. Here we use modified versions of these regression types. They are implemented through the ModifiedLinearRegression[39], ModifiedSignWeightedLinearRegression[40], and ModifiedTimeWeightedLinearRegression[41] classes on the Macrosynergy package. The term "modified" here means that predictions use regression coefficients that are adjusted for statistical precision, which tends to increase as sample sizes grow. This technique has been explained in the post How to adjust regression-based trading signals for reliability[42].

Setting cross-validation splitters and optimization criterion

Optimal selection and prediction models require cross-validation for expanding samples. To operate such learning, we must set a splitting method for the data panel available at each point in time and a statistical criterion for validation.

– **Train-test splitter:** Cross-validation compares the predictive quality of the combined selection prediction models based on multiple splits of the data into training and test sets. Each pair is called a "fold.". In the case of panel data, these splits must respect the continuity of training and test sets based on a double index of cross-sections and time periods, ensuring that all sets are sub-panels over common adjacent time spans. This was explained in the post Optimizing macro trading signals – A practical introduction[43]. Here, the splitting is governed by the ExpandingKFoldPanelSplit[44] class of the Macrosynergy package. It allows instantiating panel splitters where a fixed number of splits is implemented, but temporally adjacent panel training sets always precede test sets chronologically and where the time span of the training sets increases with the implied date of the train-test split. It is equivalent to scikit-learn's TimeSeriesSplit[45] but adapted for panels.

– **Evaluation criterion:** The metric that validates the quality of the selection-prediction models with respect to predicting target returns here is the Sharpe ratio of a stylized binary trading strategy. This is implemented by the sharpe_ratio[46] function of the Macrosynergy package. It returns a Sharpe ratio for a stylized strategy that goes long if the predictions are positive and short if the predictions are negative. It is a bit like an accuracy metric. The advantage of the Sharpe ratio versus a residuals-based criterion, such as R-squared, is that it is closer to the ultimate purpose of the model selection and a fairer basis for comparing different sets of predictors that arise from different selections across folds. If the predictors chosen across folds are unstable, then k-fold cross-validation with R-squared is more likely to result in outliers than the Sharpe ratio of a binary strategy.

Sequential learning and signal generation for each sector

For each of the 11 equity sectors, statistical learning chooses sequentially optimal combined selection prediction methods and derives related signals. These are weighted averages of the predictors, whose weights are regression coefficients adjusted for statistical precision. Sequentially here means monthly. Simply put, at the end of each month, the optimal selection-prediction method is chosen to produce a signal for each country's relative sector position at the beginning of the next month. All this is managed by the SignalOptimizer[47] class of the Macrosynergy package.

This means that for each sector, the signal-generating method, the selected predictors, and their weights change. The benefits are that hyperparameter selection is informed by empirical experience, and backtests become more objective and reliable. The drawback is that changing models and predictions become a source of instability in signals that are unrelated to markets. The graphics 8.11 - 8.16 illustrate the learning process, for example, of the relative value positions of the consumer staples sector over the past 22 years. Although data are mostly available from 2000, the analysis of learning signals typically only begins in 2003 due to meeting minimum data requirements.

The black bars in the selection map in Figure 8.11 indicate the use of various models and hyperparameter versions over time. Model change has been frequent, typically every 2-6 months. There has been a clear preference for time-weighted least-squares models, suggesting that the relevance of macro factors is seasonal, i.e., factors' predictive powers change with the economic regime, calling for greater weight of the experiences of recent months or years. The learning process also preferred relatively short lookback windows, with exponential half-lives of 1-3 years. Thus far, the learning process has not zeroed in on a single method but converged on a set of closely related time-weighted least square regressions with intercept, short half-lives and 3-7 pre-selected features.

The selection and weights of macro factors also have not yet converged in a clear and stable fashion (Figure 8.12 and Figure 8.13). This reflects that the learning process preferred models with fast-decaying lookback windows. Altogether, 35 different features have at some point been selected and applied since 2003, but 10 of them have been dominant. In recent years,

CONTENTS

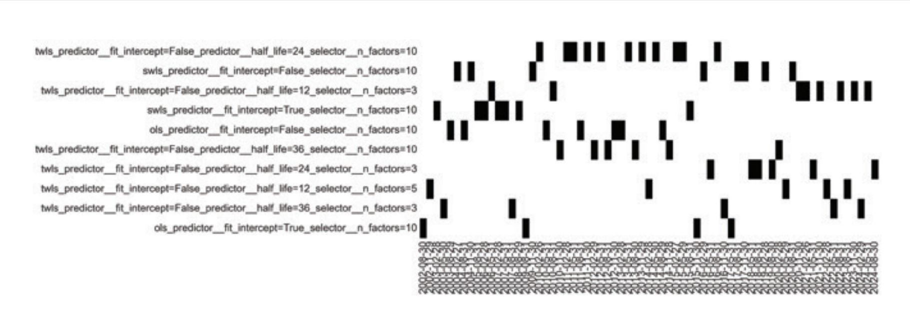


Figure 8.11: Consumer staples: model selection heatmap

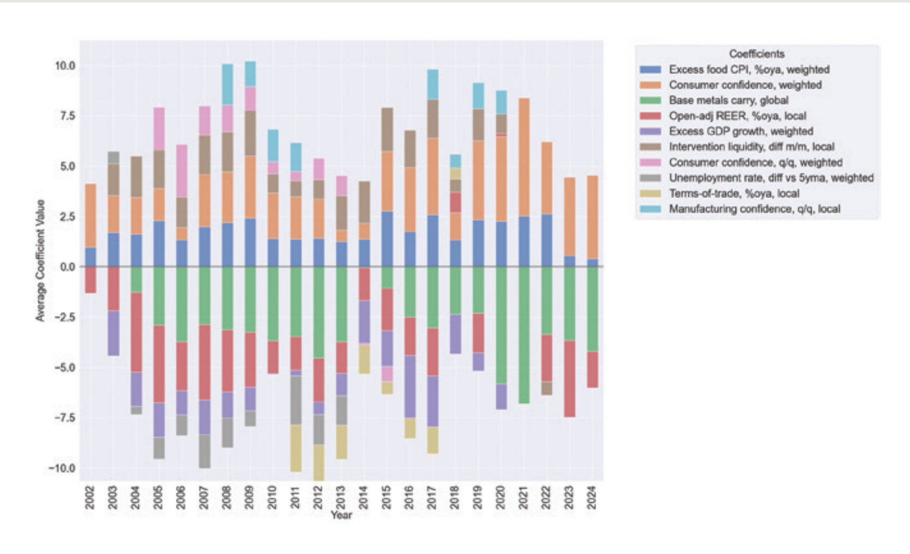


Figure 8.12: Consumer staples: annual averages of most important feature coefficients

8. Data science and macro trading factors

the main positive coefficients were given to consumer confidence (which indicates overall sentiment and financial health of households) and excess food price inflation (which siphons off purchasing power from consumer discretionary goods). The main negative coefficients have been base metals carry (which often precedes cost pickups) and real appreciation (which reduces the competitiveness of local producers versus foreign competitors).

The signal heatmap (Figure 8.14) shows that both the direction of positions and the implied risk-taking have been variable across time. Since signals conceptually apply to relative vol-targeted positions, they can be seen as a rough proxy to signal-related risk of positions. Preference for long or short positions in the energy sector has been strongly correlated across countries, which results from the influence of global factors, such as commodity inventories and prices, and international correlation of many local factors, such as manufacturing business confidence. The intensity of signals depends on the strength and alignment of selected factors.

Signal quality assessment and backtest

We apply two standard checks to assess the quality of the monthly trading signals for relative sector positions. These tests have been explained in greater detail in Evaluating macro trading signals in three simple steps[48].

Predictive power check: The first check tests the significance of the predictive power of end-of-month signals for the sector's relative returns for the next month. It looks at the statistical significance of the signal coefficient of a panel regression with period-specific random effects (Testing macro trading factors[49]). This type of regression adjusts targets and features of the predictive regression for common (global) influences. It looks at the experiences of all countries while considering common global factors in target returns and features. A relation is significant if (a) signal and subsequent returns are related over time and (b) if the country with the stronger signal relative to the cross-sectional mean tends to experience a higher subsequent return. The stronger the influence of global factors, the greater the weight of deviations from the period-mean in the regression.

The test can be implemented in Python with the CategoryRelations[50] class of the Macrosynergy package. In particular, the reg_scatter[51] method of this class displays scatter plots and regression lines in conjunction with the results of the panel regression test. The chart in Figure 8.15 illustrates the results for the example consumer staples sector (refer to Appendix 3. Equity sectors for characterization of the consumer staples sector). End-of-month learning-based signals have been positively related to subsequent relative sector returns, with a probability of significance of over 90% (Figure 8.15).

Economic value check: The second check estimates and plots the long-term cumulative naïve profit and loss of a sector relative-value strategy. Naïve PnLs can be calculated by taking positions in accordance with normalized signals and regular rebalancing at the beginning of each month, in accordance with signals at the end of the previous month, allowing for a 1-day time-lapse for trading. The trading signals here are capped at a maximum of 3 standard deviations as a reasonable risk limit. A naïve PnL does not consider transaction costs or risk management tools.

Figure 8.13: Consumer staples: feature selection heatmap

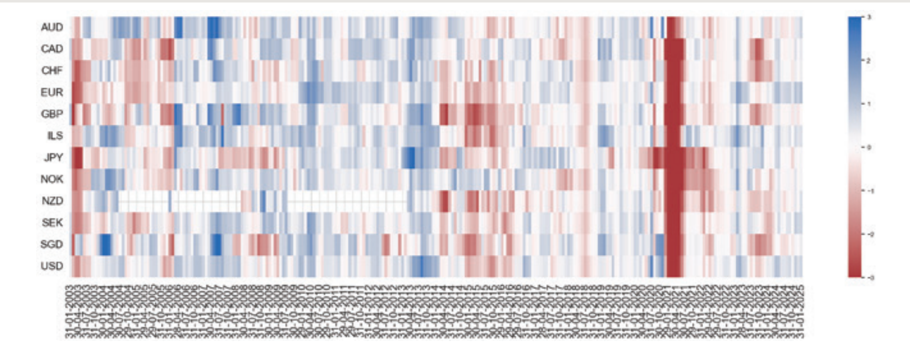


Figure 8.14: Consumer staples: signal heatmap

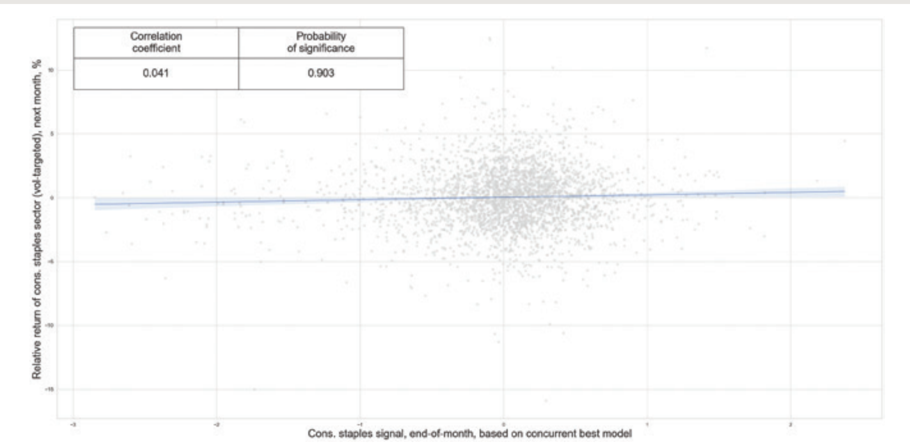


Figure 8.15: Consumer staples: learning-based signal and subsequent returns

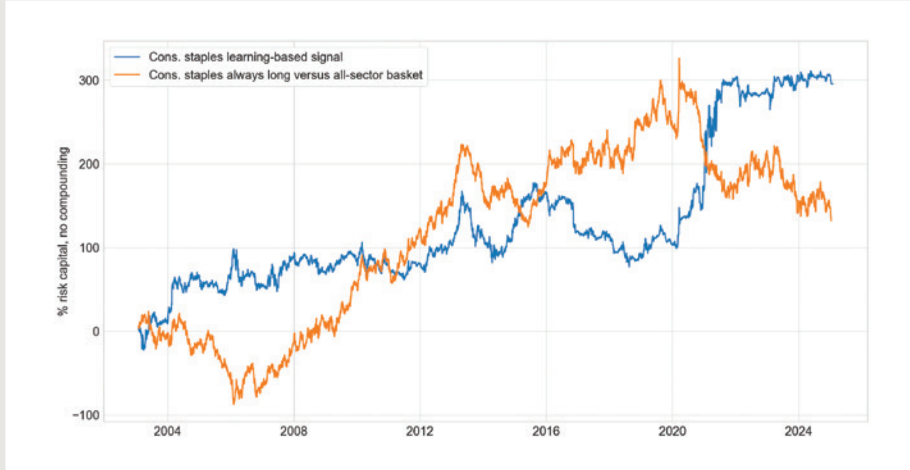


Figure 8.16: Consumer staples: naive PnLs of positions versus all-sector basket

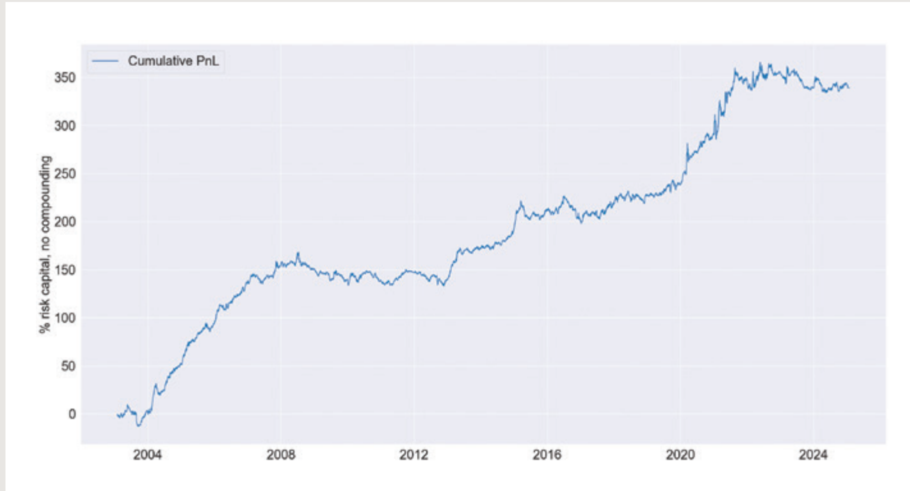


Figure 8.18: Cummulative naive PnL value of cross-sectoral equity allocation

It is thus not a realistic backtest of actual financial returns in a specific institutional setting but an objective and undistorted representation of the economic value of the signals.

The naive PnL can be calculated and plotted using the NaivePnL class of the Macrosynergy package. PnL generation has been positive overall, with a long-term Sharpe ratio of 0.8 and no correlation with the S&P500. Value generation has been seasonal, as is typical for single-principle strategies with correlated positions (Figure 8.16).

The general predictive power and PnL generation

This section evaluates the predictive power and value generation of a cross-sector relative value strategy encompassing all 11 major equity sectors. The scatters and panel tests below show consistent positive significant predictive power of learning-based signals with respect to subsequent relative sectoral returns for the 12-country panels for 10 out of 11 sectors. The probability of significance of the relation has been above 90% for 4 of the 11 sectors and above 75% for six sectors. Predictive power has been on the low side for the heavily regulated sectors of healthcare, utilities, and finance (Figure 8.17).

A global PnL relative sector strategy has been approximated by a simple unweighted average of RV PnLs for all sectors. This strategy allocates the same risk capital to the signals of all sectoral strategies, recognizing that signals are conceptually comparable and have similar orders of magnitude. This PnL can be interpreted as the value-added of the sector allocation element of a broader equity strategy.

The long-term Sharpe ratio of the global cross-sector strategy has been 1, and its Sortino ratio is 1.5. There has been almost no correlation of the PnL with equity benchmark returns (Table 8.1). Value generation has been seasonal but not heavily concentrated. The share of the best-performing 5% months in long-term PnL generation has been below 60%, which is normal for macro strategies. Considering that all aspects of value generation, from the macro indicators to the model choice, are point-in-time and free of hindsight, this is very strong evidence of the economic value behind the data and the methodology (Figure 8.18 and Table 8.1).

The long-term value generation of a cross-sector strategy based on statistical learning signals has been similar in magnitude to that of using conceptual parity signals with factors based on convention and plausibility, which was described in Macro factors and sectoral equity allocation[52].

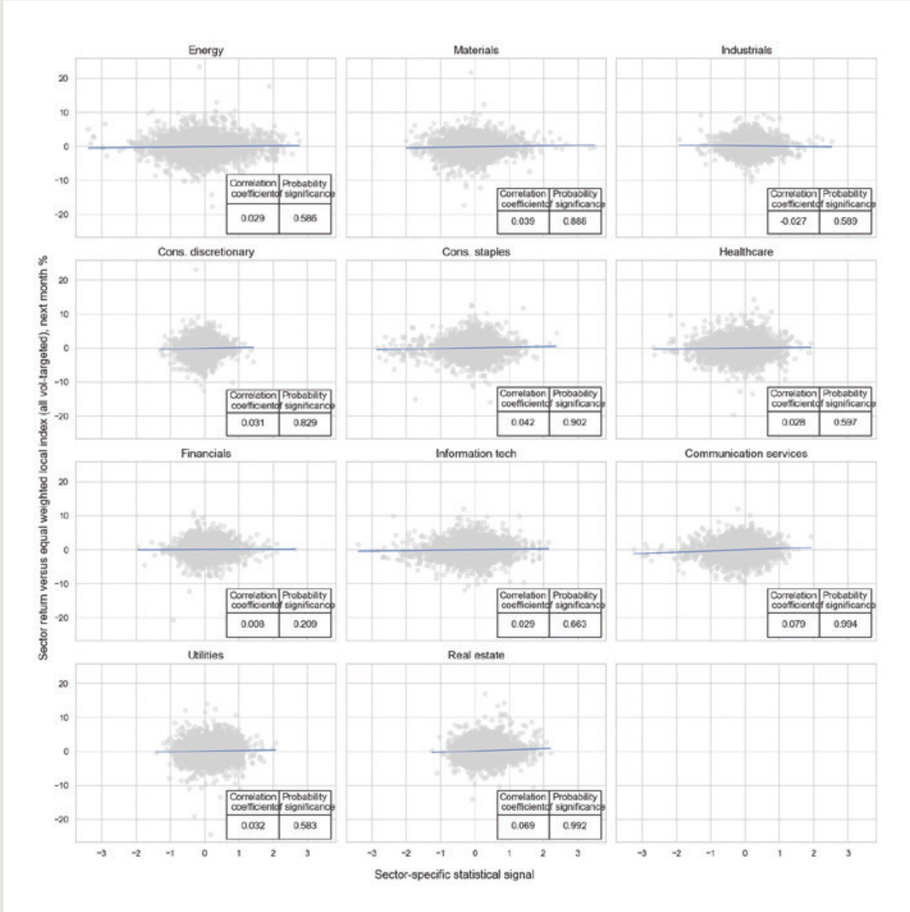


Figure 8.17: Statistical macro signals and subsequent sectoral equity returns, 11 currency areas, since 2003

CONTENTS

Category	Return %	St. Dev. %	Sharpe Ratio	Sortino Ratio	USD_ EQXR_NSA Correl
Simple average	15.16	15.09	1.00	1.49	nan
Energy	18.16	67.73	0.27	0.38	-0.08
Materials	26.22	47.27	0.55	0.82	-0.02
Industrials	-2.65	28.24	-0.09	-0.13	0.01
Cons. discretionary	15.59	29.85	0.52	0.74	-0.02
Cons. staples	13.98	33.65	0.42	0.61	-0.01
Healthcare	8.67	35.61	0.24	0.35	0.00
Financials	-1.07	43.64	-0.02	-0.04	-0.04
Information tech	6.83	33.92	0.20	0.27	-0.00
Communication services	18.51	29.46	0.63	0.91	0.01
Utilities	11.09	39.05	0.28	0.41	-0.05
Real estate	35.12	40.79	0.86	1.30	-0.04

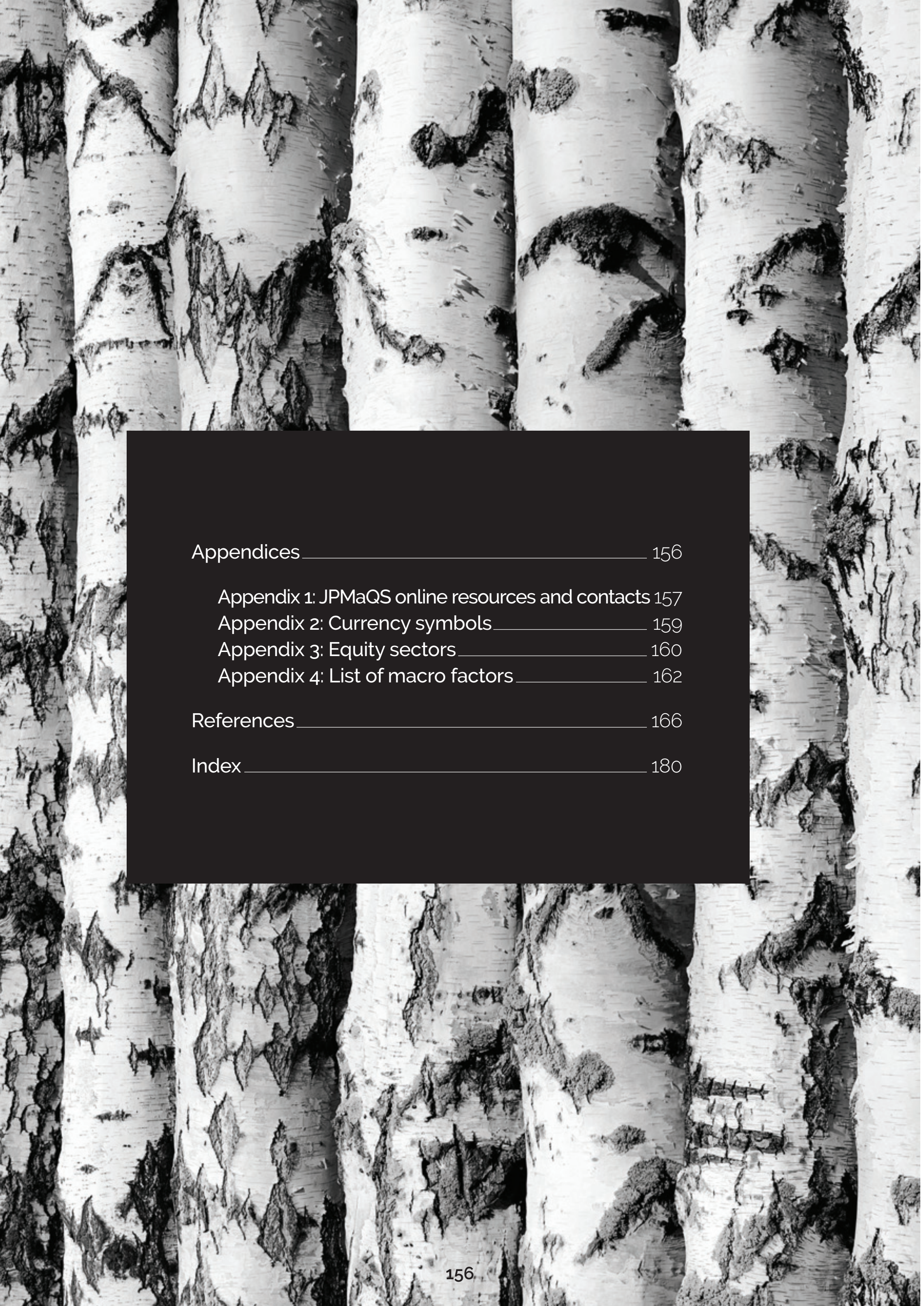
Table 8.1: Performance metrics across sectors

8.3 Other examples of using data science for macro trading

Statistical learning applications to macroeconomic data represent a relatively new and rapidly evolving field. Alongside the articles FX trading signals with regression-based learning[53] and Statistical learning for sectoral equity allocation[54] featured in this handbook, Macrosynergy has also published the following foundational posts, aimed to explore the intersection of statistical methods and macroeconomic indicators, offering practical insights for quantamental analysis (https://macrosynergy.com/academy/statistics-packages-with-quantamental-indicators):

Title	Brief summary
Optimizing macro trading signals – A practical introduction[55]	This post and its associated Jupyter Notebook demonstrate sequential signal optimization with the scikit-learn package and some specialized extensions. In particular, the post applies statistical learning to sequential optimization of three important tasks: feature selection, return prediction, and market regime classification.
Regression-based macro signals[56]	This post and its associated Jupyter Notebook provides guidance on preselecting the right regression models and hyperparameter grids based on theory and empirical evidence. It considers the advantages and disadvantages of various regression methods, including non-negative least squares, elastic net, weighted least squares, least absolute deviations, and nearest neighbors.
Using principal components to construct macro trading signals[57]	This post shows how principal components can serve as building blocks of trading signals for developed market interest rate swap positions, condensing the information of macro-quantamental indicators on inflation pressure, activity growth, and credit and money expansion. Compared to a simple combination of these categories, PCA-based statistical learning methods have produced materially higher predictive accuracy and backtested trading profits. PCA methods have also outperformed non-PCA-based regression learning. PCA-based statistical learning in backtesting leaves little scope for data mining or hindsight, and the discovery of trading value has high credibility.
How "beta learning" improves macro trading strategies[58]	This post illustrates the powerful beneficial impact of macro beta estimation and its application on an emerging market FX carry strategy.
How to adjust regressionbased trading signals for reliability[59]	This short methodological post proposes signals based on regression coefficients adjusted for statistical precision. The adjustment correctly aligns intertemporal risk-taking with the predictive power of signals. PnLs become less seasonal and outperform as sample size and statistical quality grow.
How random forests can improve macro trading signals[60]	This post shows how random forest regression can be used in a statistical learning pipeline for macro trading signals that chooses and optimizes models sequentially over time. For cross-sector equity allocation using a set of over 50 conceptual macro factors, regression trees have delivered signals with significant predictive power and economic value. Value generation has been higher and less seasonal than for statistical learning with linear regression models.

CONTENTS ⟶



Appendix 1 JPMaQS online resources and contacts

Contact information	Details
info@macrosynergy.com	Macrosynergy support
JPMaQS_support@jpmorgan.com	JPMaQS technical support at J.P.Morgan
Data_Analytics_Sales@jpmorgan.com	Sales contacts at J.P.Morgan
Relevant J.P. Morgan websites	
https://markets.jpmorgan.com/jpmm/jpmaqs	JPMaQS site on J.P.Morgan Markets (client access)
https://www.jpmorgan.com/insights/global-research/jpmaqs	JPMaQS introduction (free access)
Macrosynergy package / JPMaQS access	
https://github.com/macrosynergy/macrosynergy	Macrosynergy package GitHub repository
https://docs.macrosynergy.com	Macrosynergy package documentation
https://docs.macrosynergy.com/stable/common_definitions.html	Common definitions and terminology
https://developer.jpmorgan.com/products/dataquery_api	DataQuery documentation page
Macrosynergy academy	
https://macrosynergy.com/academy	Quantamental Academy
https://macrosynergy.com/academy/what-are-macro-quantamental-indicators	What are macro-quantamental indicators?
https://macrosynergy.com/academy/value-generation-based-on-quantamental-factors	Value generation based on quantamental factors

Macrosynergy academy	Details
https://macrosynergy.com/academy/quantamental-indicators-on-jpmaqs	Catalog of JPMaQS indicators
https://macrosynergy.com/academy/examples-macro-trading-factors	Collection of trading signals
https://macrosynergy.com/academy/statistics-packages-with-quantamental-indicators	Data science with quantamental indicators
https://macrosynergy.com/academy/introductory-tutorials	Basic tutorial for the macrosynergy package
https://macrosynergy.com/academy/academic-liaison	Macrosynergy's academic liaison program
Macrosynergy research	
https://macrosynergy.com/research	Collection of research articles and insights
Free Kaggle resources	
https://www.kaggle.com/datasets/macrosynergy/fixed-income-returns-and-macro-trends	Example dataset with quanta-mental indicators
https://www.kaggle.com/code/macrosynergy/trading-strategies-with-jpmaqs	Basic fixed income trading strategy
https://www.kaggle.com/code/macrosynergy/introduction-to-macrosynergy-package	Macrosynergy package tutorial notebook
https://www.kaggle.com/code/macrosynergy/signal-optimization-basics	Basics of optimizing trading signals
Social media	
https://www.linkedin.com/company/macrosynergy-partners	Official LinkedIn company page
https://www.linkedin.com/in/ralph-sueppel-9694188/recent-activity/all	Research and updates from Macrosynergy
https://x.com/macro_synergy	X

Appendix 2 Currency symbols

AUD..........Australian dollar
BRL..........Brazilian real
CAD..........Canadian dollar
CHF..........Swiss franc
CLP..........Chilean peso
CNY..........Chinese yuan renminbi
COP..........Colombian peso
CZK..........Czech koruna
DEM..........German mark
ESP..........Spanish peseta
EUR..........Euro
FRF..........French franc
GBP..........British pound
HKD..........Hong Kong dollar
HUF..........Hungarian forint
IDR..........Indonesian rupiah
ITL..........Italian lira
JPY..........Japanese yen
KRW..........Korean won
MXN..........Mexican peso
MYR..........Malaysian ringgit
NLG..........Dutch guilder
NOK..........Norwegian krone
NZD..........New Zealand dollar
PEN..........Peruvian sol
PHP..........Philippine peso
PLN..........Polish zloty
RON..........Romanian leu
RUB..........Russian ruble
SEK..........Swedish krona
SGD..........Singaporean dollar
THB..........Thai baht
TRY..........Turkish lira
TWD..........Taiwanese dollar
USD..........U.S. dollar
ZAR..........South African rand

Appendix 3 Equity sectors

The analysis in 8.2 Statistical learning for sectoral equity allocation (September 2024) refers to the following equity 11 sectors by the "Global Industry Classification Standards" (GICS) developed in 1999 jointly by MSCI and Standard & Poor's. The purpose of the GICS is to help asset managers classify companies and benchmark individual company performances:

Energy: The sector comprises companies that support the production and transformation of energy. There are two types. The first type focuses on exploring, producing, refining, marketing, and storing oil, gas, and consumable fuels. The second type provides equipment and services for the oil and gas industries, including drilling, well services, and related equipment manufacturing.

Materials: The sector encompasses a wide range of companies engaged in discovering, developing, and processing raw materials. These include chemicals, construction materials (such as cement and bricks), container and packaging materials (such as plastic and glass), base and precious metals, industrial minerals, paper, and other forest products.

Industrials: The sector contains a broad range of companies involved in producing goods used in construction and manufacturing (capital goods) as well as providing commercial services and transportation.

The area of capital goods includes aerospace and defence, building products, construction and engineering, electrical equipment, industrial conglomerates, and machinery. The commercial services sub-sectors include waste management, office supplies, security services, and professional services (consulting, staffing, and research). The transportation area includes air freight and logistics, airlines, marine transportation, road and rail transportation, and transportation infrastructure companies.

Consumer discretionary: This sector comprises companies producing consumer goods and services considered non-essential but desirable when disposable income is sufficient. The main areas are automobiles, consumer durables, apparel, consumer services (such as hotels and restaurants), and various retail businesses.

Consumer staples: This sector includes companies that produce and distribute presumed essential consumer products that households purchase regardless of economic conditions. These products mainly include food, beverages, household goods, and personal care items.

Health care: The sector includes companies that provide medical services, manufacture medical equipment, or produce drugs. It has two main areas. The first features health care equipment and services. It includes manufacturers of medical

products and supplies, providers of health care services (such as hospitals and nursing homes), and companies that provide technology services (such as electronic health records). The second area features research, development, and production of pharmaceuticals, biotechnology, and life sciences tools.

Financials: This sector provides financial services, including banking, investment services, insurance, and financial technology (fintech). The four main subsectors are banks, diversified financials (such as asset management, credit cards, and financial exchanges), insurance, and investment trusts.

Information technology: This sector includes companies that produce software, hardware, and semiconductors, as well as those that provide IT services, internet services, and interactive media. Software companies produce application software and systems software. Hardware companies provide computers, networking equipment, and consumer electronics. The semiconductor sector manufactures semiconductors and the equipment used for producing the former. IT services include consulting, data processing and outsourced services. Internet services encompass cloud computing, web hosting and data centres. Inter-active media include digital platforms, such as Google and Facebook.

Communication services: This sector features companies that broadly provide communication services and entertainment content. It contains two main areas. The first is telecommunication services, which provide the means for telecommunication, including traditional fixed-line telephone services, broadband internet services, and wireless telecommunication services. The second area is media and entertainment, which focuses on the creation and distribution of content for broadcasting, home entertainment, movies, music, video games, social media platforms, search engines, and so forth.

Utilities: This sector includes companies that provide essential utility services such as electricity and water. Their activities include generation, transmission, and distribution, and they are typically subject to tight regulations. Standard classification distinguishes five types of utilities: electric utilities, gas utilities, water utilities, multi-utilities, and independent power and renewable electricity producers.

Real estate: This sector focuses on real estate development and operation. It encompasses property ownership, development, management, and leasing. It also includes Real Estate Investment Trusts (REITs) that invest in various property types.

Appendix 4 List of macro factors

View Appendix 3. Equity sectors for sector descriptions.

Category	Label	Description	Geogr.
Business surveys			
CBCSCORE_SA_D3M3ML3_WG_ZN	Construction confidence, q/q	Construction business confidence score, seas. adjusted, change q/q	weighted
CBCSCORE_SA_D3M3ML3_ZN	Construction confidence, q/q	Construction business confidence score, seas. adjusted, change q/q	local
CBCSCORE_SA_WG_ZN	Construction confidence	Construction business confidence score, seas. adjusted	weighted
CBCSCORE_SA_ZN	Construction confidence	Construction business confidence score, seas. adjusted	local
MBCSCORE_SA_D3M3ML3_WG_ZN	Manufacturing confidence, q/q	Manufacturing business confidence score, seas. adj., change q/q	weighted
MBCSCORE_SA_D3M3ML3_ZN	Manufacturing confidence, q/q	Manufacturing business confidence score, seas. adj., change q/q	local
MBCSCORE_SA_WG_ZN	Manufacturing confidence	Manufacturing business confidence score, seasonally adjusted	weighted
MBCSCORE_SA_ZN	Manufacturing confidence	Manufacturing business confidence score, seasonally adjusted	local
SBCSCORE_SA_D3M3ML3_WG_ZN	Service confidence, q/q	Services business confidence score, seas. adjusted, change q/q	weighted
SBCSCORE_SA_D3M3ML3_ZN	Service confidence, q/q	Services business confidence score, seas. adjusted, change q/q	local
SBCSCORE_SA_WG_ZN	Service confidence	Services business confidence score, seasonally adjusted	weighted
SBCSCORE_SA_ZN	Service confidence	Services business confidence score, seasonally adjusted	local

Category	Label	Description	Geogr.
Commodity inventories			
BASEXINVCSCORE_SA_ZN	Excess crude inventory score	Crude oil excess inventory z-score, seasonally adjusted	global
BMLXINVCSCORE_SA_ZN	Excess metal inventory score	Base metal excess inventory z-score, seasonally adjusted	global
REFIXINVCSCORE_SA_ZN	Excess refined oil inventory score	Refined oil product excess inventory z-score, seas. adjusted	global
Debt			
CORPINTNETGDP_SA_D1Q1QL4_WG_ZN	Corporate debt servicing, %oya	Corporate net debt servicing-to-GDP ratio, seasonally-adjusted, %oya	weighted
CORPINTNETGDP_SA_D1Q1QL4_ZN	Corporate debt servicing, %oya	Corporate net debt servicing-to-GDP ratio, seasonally-adjusted, %oya	local
HHINTNETGDP_SA_D1M1ML12_WG_ZN	Households debt servicing, %oya	Households net debt servicing-to-GDP ratio, seasonally-adjusted, %oya	weighted
HHINTNETGDP_SA_D1M1ML12_ZN	Households debt servicing, %oya	Households net debt servicing-to-GDP ratio, seasonally-adjusted, %oya	local
XGGDGDPRATIOX10_NSA_ZN	Excess projected gov. debt	Government debt-to-GDP ratio proj. in 10 years, in excess of 100%	local
Exports			
XEXPORTS_SA_P1M1ML12_3MMA_ZN	Excess export growth	Exports growth, %oya, 3mma, in excess of 5-year median GDP growth	local
Inflation - broad			
XCPIC_SA_P1M1ML12_ZN	Excess core CPI, %oya	Core CPI, %oya, in excess of effective inflation target	local
XCPIH_SA_P1M1ML12_ZN	Excess headline CPI, %oya	Headline CPI, %oya, in excess of effective inflation target	local
XPPIH_NSA_P1M1ML12_ZN	Excess PPI, %oya	Producer price inflation, %oya, in excess of eff. inflation target	local
Inflation - specific			
XCPIE_SA_P1M1ML12_WG_ZN	Excess energy CPI, %oya	Energy CPI, %oya, in excess of effective inflation target	weighted
XCPIE_SA_P1M1ML12_ZN	Excess energy CPI, %oya	Energy CPI, %oya, in excess of effective inflation target	local
XCPIF_SA_P1M1ML12_WG_ZN	Excess food CPI, %oya	Food CPI, %oya, in excess of effective inflation target	weighted
XCPIF_SA_P1M1ML12_ZN	Excess food CPI, %oya	Food CPI, %oya, in excess of effective inflation target	local

Category	Label	Description	Geogr.
Labor market			
UNEMPLRATE_NSA_3MMA_D1M1ML12_WG_ZN	Unemployment rate, diff oya	Unemployment rate, change oya	weighted
UNEMPLRATE_NSA_3MMA_D1M1ML12_ZN	Unemployment rate, diff oya	Unemployment rate, change oya	local
UNEMPLRATE_SA_3MMAv5YMA_WG_ZN	Unemployment rate, diff vs 5yma	Unemployment rate, difference vs 5-year moving average	weighted
UNEMPLRATE_SA_3MMAv5YMA_ZN	Unemployment rate, diff vs 5yma	Unemployment rate, difference vs 5-year moving average	local
XEMPL_NSA_P1M1ML12_3MMA_WG_ZN	Excess employment growth	Employment growth, %oya, 3mma, in excess of population growth	weighted
XEMPL_NSA_P1M1ML12_3MMA_ZN	Excess employment growth	Employment growth, %oya, 3mma, in excess of population growth	local
XRWAGES_NSA_P1M1ML12_ZN	Excess real wage growth	Real wage growth, %oya, in excess of medium-term productivity growth	local
Market metrics			
BMLCOCRY_SAVT10_21DMA_ZN	Base metals carry	Nominal carry for base metals basket, seas and vol-adjusted, 21 days MA	global
COXR_VT10vWTI_21DMA_ZN	Refined vs crude oil returns	Refined oil products vs crude oil vol-targeted return diff, 21 days MA	global
RIR_NSA_ZN	Real 1-month rate	Real 1-month interest rate	local
RSLOPEMIDDLE_NSA_ZN	Real 5y-2y yield	Real IRS yield differentials, 5-years versus 2-years	local
RYLDIRS02Y_NSA_ZN	Real 2-year yield	Real 2-year IRS yield	local
RYLDIRS05Y_NSA_ZN	Real 5-year yield	Real 5-year IRS yield	local
Output growth			
XCSTR_SA_P1M1ML12_3MMA_WG_ZN	Excess construction growth	Construction output, %oya, 3mma, in excess of 5-y median GDP growth	weighted
XCSTR_SA_P1M1ML12_3MMA_ZN	Excess construction growth	Construction output, %oya, 3mma, in excess of 5-y median GDP growth	local
XIP_SA_P1M1ML12_3MMA_WG_ZN	Excess industry growth	Industrial output, %oya, 3mma, in excess of 5-y median GDP growth	weighted
XIP_SA_P1M1ML12_3MMA_ZN	Excess industry growth	Industrial output, %oya, 3mma, in excess of 5-y median GDP growth	local
XRGDPTECH_SA_P1M1ML12_3MMA_WG_ZN	Excess GDP growth	Real GDP, %oya, 3mma, using HF data, in excess of 5-y med. GDP growth	weighted
XRGDPTECH_SA_P1M1ML12_3MMA_ZN	Excess GDP growth	Real GDP, %oya, 3mma, using HF data, in excess of 5-y med. GDP growth	local

Category	Label	Description	Geogr.
Private consumption			
CCSCORE_SA_D3M3ML3_WG_ZN	Consumer confidence, q/q	Consumer confidence score, seasonally adjusted, change q/q	weighted
CCSCORE_SA_D3M3ML3_ZN	Consumer confidence, q/q	Consumer confidence score, seasonally adjusted, change q/q	local
CCSCORE_SA_WG_ZN	Consumer confidence	Consumer confidence score, seasonally adjusted	weighted
CCSCORE_SA_ZN	Consumer confidence	Consumer confidence score, seasonally adjusted	local
XNRSALES_SA_P1M1ML12_3MMA_WG_ZN	Excess retail sales growth	Nominal retail sales, %oya, 3mma, in excess of 5-y median GDP growth	weighted
XNRSALES_SA_P1M1ML12_3MMA_ZN	Excess retail sales growth	Nominal retail sales, %oya, 3mma, in excess of 5-y median GDP growth	local
XRPCONS_SA_P1M1ML12_3MMA_WG_ZN	Excess consumption growth	Real private consumption, %oya, 3mma, in excess of 5-y median GDP growth	weighted
XRPCONS_SA_P1M1ML12_3MMA_ZN	Excess real consum growth	Real private consumption, %oya, 3mma, in excess of 5-y median GDP growth	local
XRRSALES_SA_P1M1ML12_3MMA_WG_ZN	Excess real retail growth	Real retail sales, %oya, 3mma, in excess of 5-y median GDP growth	weighted
XRRSALES_SA_P1M1ML12_3MMA_ZN	Excess real retail growth	Real retail sales, %oya, 3mma, in excess of 5-y median GDP growth	local
Private credit			
INTLIQGDP_NSA_D1M1ML1_ZN	Intervention liquidity, diff m/m	Intervention liquidity to GDP ratio, change over the last month	local
INTLIQGDP_NSA_D1M1ML6_ZN	Intervention liquidity, diff 6m	Intervention liquidity to GDP ratio, change overlast 6 months	local
XPCREDITBN_SJA_P1M1ML12_WG_ZN	Excess credit growth	Private credit, %oya, 3mma, in excess of 5-y median GDP growth	weighted
XPCREDITBN_SJA_P1M1ML12_ZN	Excess credit growth	Private credit, %oya, 3mma, in excess of 5-y median GDP growth	local
Real appreciation			
CMPI_NSA_P1M12ML1_ZN	Import prices, %oya	Commodity-based import price index, %oya	local
CTOT_NSA_P1M12ML1_ZN	Terms-of-trade, %oya	Commodity-based terms-of-trade, %oya	local
CXPI_NSA_P1M12ML1_ZN	Export prices, %oya	Commodity-based export price index, %oya	local
REEROADJ_NSA_P1M12ML1_ZN	Open-adj REER, %oya	Openness-adjusted real effective exchange rate, %oya	local

CONTENTS

References

Part One

1. Introduction

1 https://macrosynergy.com/research/how-macro-quantamental-trading-signals-will-transform-asset-management
2 Chapter 4: The J.P. Morgan Macrosynergy Quantamental System
3 Chapter 2: Macro information waste and the quantamental solution
4 https://macrosynergy.com/research/considering-rational-inattention-for-trading-strategies
5 Chapter 5: Value generation based on quantamental indicators
6 Section 5.1: Using macro trends
7 Section 5.2: Detecting implicit subsidies
8 Section 5.3: Estimating price distortions
9 Section 5.4: Endogenous market risk
10 https://macrosynergy.com/academy
11 https://macrosynergy.com/research/macroeconomic-cycles-and-asset-class-returns
12 https://macrosynergy.com/research/intervention-liquidity
13 https://macrosynergy.com/research/equity-versus-fixed-income-the-predictive-power-of-bank-surveys
14 https://macrosynergy.com/research/trend-following-combining-market-and-macro-information
15 https://macrosynergy.com/research/equity-trend-following-and-macro-headwinds
16 https://macrosynergy.com/research/fx-and-macro-headwinds
17 https://macrosynergy.com/research/modified-and-balanced-fx-carry
18 https://macrosynergy.com/research/advanced-fx-carry-strategies-with-valuation-adjustment
19 https://macrosynergy.com/research/modified-and-balanced-fx-carry
20 https://macrosynergy.com/research/commodity-carry-as-a-trading-signal-part-2
21 https://macrosynergy.com/research/macro-trends-and-equity-allocation-a-brief-introduction
22 https://macrosynergy.com/research/macro-factors-and-sectoral-equity-allocation
23 https://macrosynergy.com/research/cross-country-equity-futures-strategies
24 https://macrosynergy.com/research/macro-information-changes
25 https://macrosynergy.com/research/optimal-signals
26 https://macrosynergy.com/research/regression-signals
27 https://macrosynergy.com/research/fx-trading-signals-with-regression-based-learning
28 https://macrosynergy.com/research/how-to-adjust-regression-based-trading-signals-for-reliability

2. Macro information waste and the quantamental solution

1 https://macrosynergy.com/research/macro-information-waste-and-the-quantamental-solution
2 https://macrosynergy.com/research/riherding
3 https://macrosynergy.com/research/efficient-use-of-u-s-jobless-claims-reports
4 https://macrosynergy.com/research/information-inattentiveness-of-financial-markets
5 https://macrosynergy.com/research/sticky-expectations-and-predictable-equity-returns
6 https://macrosynergy.com/research/risk-premia-strategies
7 https://macrosynergy.com/research/the-dominance-of-price-over-value
8 https://macrosynergy.com/research/information-inefficiency-in-market-experiments
9 https://macrosynergy.com/research/a-theory-of-information-inefficiency-of-markets
10 https://macrosynergy.com/research/understanding-bid-offer-spreads-in-otc-markets
11 https://macrosynergy.com/research/the-irrational-neglect-of-optimal-betting-strategies
12 https://macrosynergy.com/research/retail-investor-beliefs
13 https://macrosynergy.com/research/how-u-s-mutual-funds-reallocate-assets
14 https://macrosynergy.com/research/factor-investment-in-government-bonds
15 https://macrosynergy.com/research/concerns-over-risk-parity-trading-strategies
16 https://macrosynergy.com/research/the-passive-investment-boom-and-its-consequences
17 https://macrosynergy.com/research/fake-alpha
18 https://macrosynergy.com/research/trend-following-in-u-s-equities
19 https://macrosynergy.com/research/a-basic-theory-of-momentum-strategies
20 https://macrosynergy.com/research/herding-in-financial-markets
21 https://macrosynergy.com/research/a-theory-of-herding-and-instability-in-bond-markets
22 https://macrosynergy.com/research/fundamental-trend-following
23 https://macrosynergy.com/research/overconfidence-and-inattention-as-asset-return-factors
24 https://macrosynergy.com/research/why-financial-markets-misprice-fundamental-value
25 https://macrosynergy.com/research/what-markets-can-learn-from-statistical-learning
26 https://macrosynergy.com/research/the-misinterpretation-of-exchange-rate-fundamentals
27 https://macrosynergy.com/research/the-uncorrelatedness-of-equity-and-fx-returns
28 Section 5.1: Macro trends
29 Section 5.2: Implicit subsidies
30 Section 5.4: Endogenous market risk

3. Understanding macro-quantamental indicators

1 https://macrosynergy.com/academy/what-are-macro-quantamental-indicators

4. The J.P. Morgan Macrosynergy Quantamental System

1 https://macrosynergy.com/academy/quantamental-indicators-on-jpmaqs
2 https://www.jpmorgan.com/insights/global-research/markets/macrosynergy-quantamental-system

5. Value generation based on quantamental indicators

1 https://macrosynergy.com/research/macro-efficiency
2 https://macrosynergy.com/research/considering-rational-inattention-for-trading-strategies
3 https://macrosynergy.com/academy/value-generation-based-on-quantamental-factors
4 https://macrosynergy.com/research/macrotrends-2
5 https://macrosynergy.com/research/how-loss-aversion-affects-market-volatility-and-returns
6 https://macrosynergy.com/research/the-short-term-effects-of-u-s-economic-data-releases
7 https://macrosynergy.com/research/macroeconomic-news-and-bond-price-trends
8 https://macrosynergy.com/research/excess-inflation-and-asset-class-returns
9 https://macrosynergy.com/research/macro-demand-based-rates-strategies
10 https://macrosynergy.com/research/merchandise-import-as-predictor-of-duration-returns
11 https://macrosynergy.com/research/u-s-treasuries-decomposing-the-yield-curve-and-predicting-returns
12 https://macrosynergy.com/research/treasury-yield-curve-and-macro-trends

13 https://macrosynergy.com/research/an-equilibrium-theory-of-treasury-yields
14 https://macrosynergy.com/research/a-model-for-bond-risk-premia-and-the-macroeconomy
15 https://macrosynergy.com/research/the-demographic-compression-of-interest-rates
16 https://macrosynergy.com/research/the-secular-decline-in-the-global-equilibrium-real-interest-rate
17 https://macrosynergy.com/research/economic-growth-and-fx-forward-returns
18 https://macrosynergy.com/research/fx-trading-strategies-based-on-output-gaps
19 https://macrosynergy.com/research/pure-macro-fx-strategies-the-benefits-of-double-diversification
20 https://macrosynergy.com/research/modified-and-balanced-fx-carry
21 https://macrosynergy.com/research/fx-and-macro-headwinds
22 https://macrosynergy.com/research/a-rule-of-thumb-for-exchange-rate-trends
23 https://macrosynergy.com/research/understanding-international-capital-flows-and-shocks
24 https://macrosynergy.com/research/external-imbalances-and-fx-returns
25 https://macrosynergy.com/research/equity-trend-following-and-macro-headwinds
26 https://macrosynergy.com/research/equity-consumption
27 https://macrosynergy.com/research/inflation-and-equity-markets
28 https://macrosynergy.com/research/equity-ratios-and-credit-spreads-the-inflation-effect
29 https://macrosynergy.com/research/equity-versus-fixed-income-the-predictive-power-of-bank-surveys
30 https://macrosynergy.com/research/intervention-liquidity
31 https://macrosynergy.com/research/macro-uncertainty-as-predictor-of-market-volatility
32 https://macrosynergy.com/research/macro-factors-and-sectoral-equity-allocation/
33 https://macrosynergy.com/research/equity-factor-timing-with-macro-trends
34 https://macrosynergy.com/research/factor-timing
35 https://macrosynergy.com/research/factor-momentum-a-brief-introduction
36 https://macrosynergy.com/research/equity-convexity-and-gamma-strategies
37 https://macrosynergy.com/research/forecasting-energy-markets-with-macro-data
38 https://macrosynergy.com/research/predicting-base-metal-futures-returns-with-economic-data
39 https://macrosynergy.com/research/business-sentiment-and-commodity-future-returns
40 https://macrosynergy.com/research/the-drivers-of-commodity-cycles
41 https://macrosynergy.com/research/inflation-and-precious-metal-prices
42 https://macrosynergy.com/research/tracking-systematic-macro-default-risk
43 https://macrosynergy.com/research/sovereign-debt-sustainability-and-cds-returns
44 https://macrosynergy.com/research/the-macro-forces-behind-equity-bond-price-correlation
45 https://macrosynergy.com/research/understanding-dollar-shortages-and-related-market-dynamics
46 https://macrosynergy.com/research/the-fall-of-inflation-compensation
47 https://macrosynergy.com/research/china-housing-and-global-base-metal-prices
48 https://macrosynergy.com/research/using-commodity-prices-to-predict-exchange-rates
49 https://macrosynergy.com/research/how-to-use-financial-conditions-indices
50 https://macrosynergy.com/research/fx-forward-hedging-in-macro-trading
51 https://macrosynergy.com/research/how-beta-learning-improves-macro-trading-strategies

52 https://macrosynergy.com/research/how-to-measure-economic-uncertainty
53 https://macrosynergy.com/research/the-drivers-of-commodity-price-volatility
54 https://macrosynergy.com/research/fx-returns-and-external-balances
55 https://macrosynergy.com/research/treasury-yield-curve-and-macro-trends
56 https://macrosynergy.com/research/u-s-natural-interest-rate-stuck-at-0-evidence-and-consequences
57 https://macrosynergy.com/research/tradable-economics
58 https://macrosynergy.com/research/monetary-policy-stance-in-one-indicator
59 https://macrosynergy.com/research/forecasting-inflation-under-globalisation
60 https://macrosynergy.com/research/simple-macroeconomics-for-trading
61 https://macrosynergy.com/research/simple-international-macroeconomics-for-trading
62 https://macrosynergy.com/research/dimension-reduction-for-macro-forecasting-the-basics
63 https://macrosynergy.com/research/nowcasting-gdp-growth
64 https://macrosynergy.com/research/tracking-trends-in-em-economies
65 https://macrosynergy.com/research/building-international-financial-conditions-indices
66 https://macrosynergy.com/research/forecasting-inflation-under-globalisation
67 https://macrosynergy.com/research/understanding-capital-flow-deflection
68 https://macrosynergy.com/research/inflationrisk
69 https://macrosynergy.com/research/commodity-trends-as-predictors-of-bond-returns
70 https://macrosynergy.com/research/the-importance-of-differentiating-types-of-oil-price-shocks
71 https://macrosynergy.com/research/commodity-terms-of-trade
72 https://macrosynergy.com/research/vix-term-structure-as-a-trading-signal
73 https://macrosynergy.com/research/using-yield-curve-information-for-fx-trading
74 https://macrosynergy.com/research/liquidity-yields-and-fx
75 https://macrosynergy.com/research/treasury-basis-and-dollar-overshooting
76 https://macrosynergy.com/research/policy-rates-and-equity-volatility
77 https://macrosynergy.com/research/cds-term-premia-and-exchange-rates
78 https://macrosynergy.com/research/the-dollar-as-barometer-for-credit-market-risk
79 https://macrosynergy.com/research/how-to-construct-a-bond-volatility-index-and-extract-market-information
80 https://macrosynergy.com/research/six-ways-to-estimate-realized-volatility
81 https://macrosynergy.com/research/predicting-volatility-with-heterogeneous-autoregressive-models
82 https://macrosynergy.com/research/what-we-can-learn-from-market-price-volatility
83 https://macrosynergy.com/research/measuring-non-conventional-monetary-policy-surprises
84 https://macrosynergy.com/research/fed-policy-shocks-and-foreign-currency-risk-premia
85 https://macrosynergy.com/research/the-global-effects-of-a-u-s-term-premium-shock
86 https://macrosynergy.com/research/inflation-differentials-and-equity-returns
87 https://macrosynergy.com/research/policy-rates-and-equity-returns-the-slope-factor
88 https://macrosynergy.com/research/fx-returns-and-external-balances-2
89 https://macrosynergy.com/research/the-price-effects-of-order-flow
90 https://macrosynergy.com/research/why-and-when-central-banks-intervene-in-fx-markets
91 https://macrosynergy.com/research/the-mighty-long-long-trade
92 https://macrosynergy.com/research/commodity-pricing
93 https://macrosynergy.com/research/multiple-risk-free-interest-rates

94 https://macrosynergy.com/research/convenience-yield-risk-premia
95 https://macrosynergy.com/research/basics-of-market-liquidity-risk
96 https://macrosynergy.com/research/how-salience-theory-explains-the-mispricing-of-risk
97 https://macrosynergy.com/research/fear-of-drawdown
98 https://macrosynergy.com/research/what-variance-swaps-tell-us-about-risk-premia
99 https://macrosynergy.com/research/the-long-term-rise-in-risk-spreads
100 https://macrosynergy.com/research/prospect-theory-value-as-investment-factor
101 https://macrosynergy.com/research/how-loss-aversion-affects-market-volatility-and-returns
102 https://macrosynergy.com/research/the-risk-reversal-premium
103 https://macrosynergy.com/research/predicting-equity-returns
104 https://macrosynergy.com/research/the-1x1-of-risk-perception-measures
105 https://macrosynergy.com/research/fx-risk-and-local-em-bond-yields
106 https://macrosynergy.com/research/active-fund-risk-premia-in-emerging-markets
107 https://macrosynergy.com/research/fake-alpha
108 https://macrosynergy.com/research/cross-asset-carry-an-introduction
109 https://macrosynergy.com/research/how-to-use-fx-carry-in-trading-strategies
110 https://macrosynergy.com/research/official-flows-and-consequences-for-fx-markets
111 https://macrosynergy.com/research/explaining-fx-forward-bias
112 https://macrosynergy.com/research/how-banks-dollar-holdings-drive-exchange-rate-dynamics
113 https://macrosynergy.com/research/disaster-risk-and-currency-returns
114 https://macrosynergy.com/research/volatility-risk-premia-and-fx-returns
115 https://macrosynergy.com/research/the-nature-and-risks-of-em-fx-carry-trades
116 https://macrosynergy.com/research/understanding-the-dollar-cross-currency-basis
117 https://macrosynergy.com/research/understanding-dollar-shortages-and-related-market-dynamics
118 https://macrosynergy.com/research/self-fulfilling-and-self-destructing-fx-carry-trades
119 https://macrosynergy.com/research/how-to-use-fx-carry-in-trading-strategies
120 https://macrosynergy.com/research/modified-and-balanced-fx-carry
121 https://macrosynergy.com/research/advanced-fx-carry-strategies-with-valuation-adjustment
122 https://macrosynergy.com/research/fx-strategies-based-on-quanto-contract-information
123 https://macrosynergy.com/research/multiple-risk-free-interest-rates
124 https://macrosynergy.com/research/the-predictive-power-of-real-government-bond-yields
125 https://macrosynergy.com/research/fixed-income-carry-as-a-trading-signal
126 https://macrosynergy.com/research/the-fall-of-inflation-compensation
127 https://macrosynergy.com/research/duration-volatility-risk-premia
128 https://macrosynergy.com/research/the-illiquidity-risk-premium
129 https://macrosynergy.com/research/commodity-carry-as-a-trading-signal-part-1
130 https://macrosynergy.com/research/commodity-carry
131 https://macrosynergy.com/research/seasonal-effects-in-commodity-futures-curves
132 https://macrosynergy.com/research/commodity-pricing
133 https://macrosynergy.com/research/understanding-convenience-yields

134 https://macrosynergy.com/research/commodity-trading-strategies-and-convenience-yields
135 https://macrosynergy.com/research/risk-premia-in-energy-futures-markets
136 https://macrosynergy.com/research/commodity-futures-curves-and-risk-premia
137 https://macrosynergy.com/research/volatility-risk-premia-in-the-commodity-space
138 https://macrosynergy.com/research/lessons-from-long-term-global-equity-performance
139 https://macrosynergy.com/research/understanding-and-dissecting-the-variance-risk-premium
140 https://macrosynergy.com/research/variance-term-premia
141 https://macrosynergy.com/research/the-correlation-risk-premium
142 https://macrosynergy.com/research/the-low-risk-effect-evidence-and-reason
143 https://macrosynergy.com/research/the-low-risk-effect-and-macro-trading-strategies
144 https://macrosynergy.com/research/the-basics-of-low-risk-strategies
145 https://macrosynergy.com/research/the-emotion-beta-of-stocks
146 https://macrosynergy.com/research/statistical-arbitrage-risk-premium
147 https://macrosynergy.com/research/how-growing-assets-under-management-can-compromise-investment-strategies
148 https://macrosynergy.com/research/volatility-markets-a-practitioners-view
149 https://macrosynergy.com/research/variance-risk-premia-for-patient-investors
150 https://macrosynergy.com/research/realistic-volatility-risk-premia
151 https://macrosynergy.com/research/volatility-insurance-and-exchange-rate-predictability
152 https://macrosynergy.com/research/gold-risk-premium-and-return
153 https://macrosynergy.com/research/the-importance-of-volatility-of-volatility
154 https://macrosynergy.com/research/variance-term-premia
155 https://macrosynergy.com/research/the-downside-variance-risk-premium
156 https://macrosynergy.com/research/the-importance-of-volatility-of-volatility
157 https://macrosynergy.com/research/the-mighty-long-long-trade
158 https://macrosynergy.com/research/macro-factors-for-the-risk-parity-trade
159 https://macrosynergy.com/research/price-distortions-2
160 https://macrosynergy.com/research/the-price-effects-of-order-flow
161 https://macrosynergy.com/research/high-speed-trading-lessons-from-quantum-physics
162 https://macrosynergy.com/research/market-noise
163 https://macrosynergy.com/research/equity-return-anomalies-and-their-causes
164 https://macrosynergy.com/research/building-a-real-time-market-distress-index
165 https://macrosynergy.com/research/identifying-asset-price-bubbles
166 https://macrosynergy.com/research/how-to-recognize-an-asset-price-bubble
167 https://macrosynergy.com/research/explosive-dynamics-in-exchange-rates
168 https://macrosynergy.com/research/detecting-price-distortions-with-neural-networks
169 https://macrosynergy.com/research/fixed-income-relative-value-basics
170 https://macrosynergy.com/research/trend-following-in-u-s-equities
171 https://macrosynergy.com/research/herding-in-financial-markets
172 https://macrosynergy.com/research/why-and-when-financial-markets-are-herding
173 https://macrosynergy.com/research/credit-market-herding-and-price-distortions
174 https://macrosynergy.com/research/beta-herding
175 https://macrosynergy.com/research/the-risk-of-statistical-risk-measures

176 https://macrosynergy.com/research/how-statistical-risk-models-increase-financial-crisis-risk
177 https://macrosynergy.com/research/quantitative-easing-and-var-shocks
178 https://macrosynergy.com/research/the-volatility-feedback-loop
179 https://macrosynergy.com/research/overshooting-of-u-s-treasury-yields
180 https://macrosynergy.com/research/how-the-fed-has-reduced-the-risk-of-convexity-events
181 https://macrosynergy.com/research/why-cds-spreads-can-decouple-from-fundamentals
182 https://macrosynergy.com/research/how-fear-of-disaster-affects-financial-markets
183 https://macrosynergy.com/research/how-salience-theory-explains-the-mispricing-of-risk
184 https://macrosynergy.com/research/corporate-bond-market-momentum-a-model
185 https://macrosynergy.com/research/mutual-fund-flows-and-fire-sale-risk
186 https://macrosynergy.com/research/how-equity-return-expectations-contribute-to-bubbles
187 https://macrosynergy.com/research/fixed-income-relative-value-basics
188 https://macrosynergy.com/research/broker-dealer-leverage-drives-credit-and-equity-prices
189 https://macrosynergy.com/research/basics-of-market-liquidity-risk
190 https://macrosynergy.com/research/the-illiquidity-risk-premium
191 https://macrosynergy.com/research/how-poor-liquidity-creates-rational-price-distortions
192 https://macrosynergy.com/research/market-liquidity-basics-and-concerns
193 https://macrosynergy.com/research/bond-market-liquidity-risks
194 https://macrosynergy.com/research/the-volcker-rule-and-liquidity-risk
195 https://macrosynergy.com/research/euro-area-shadow-banking-and-risks
196 https://macrosynergy.com/research/shocks-and-flows-in-international-equity-and-bond-markets
197 https://macrosynergy.com/research/institutional-cash-hoarding-and-market-dynamics
198 https://macrosynergy.com/research/some-stylized-facts-of-fx-liquidity
199 https://macrosynergy.com/research/covered-interest-parity-breakdowns-and-opportunities
200 https://macrosynergy.com/research/why-the-covered-interest-parity-is-breaking-down
201 https://macrosynergy.com/research/the-risk-adjusted-covered-interest-parity
202 https://macrosynergy.com/research/dealer-balance-sheets-and-market-liquidity
203 https://macrosynergy.com/research/the-asymmetry-of-government-bond-returns
204 https://macrosynergy.com/research/liquidity-risk-in-european-bond-markets
205 https://macrosynergy.com/research/the-pitfalls-of-emerging-markets-asset-management
206 https://macrosynergy.com/research/how-em-bond-funds-increase-market-volatility
207 https://macrosynergy.com/research/on-the-vulnerability-of-local-emerging-debt-markets
208 https://macrosynergy.com/research/market-noise
209 https://macrosynergy.com/research/inefficient-benchmarking-and-trading-opportunities
210 https://macrosynergy.com/research/the-low-risk-effect-and-macro-trading-strategies
211 https://macrosynergy.com/research/passive-investment-vehicles-rise-and-fallout
212 https://macrosynergy.com/research/a-primer-on-benchmark-index-effects
213 https://macrosynergy.com/research/pension-funds-and-herding
214 https://macrosynergy.com/research/the-global-systemic-consequences-of-solvency-ii

215 https://macrosynergy.com/research/how-bank-regulatory-reform-has-changed-macro-trading
216 https://macrosynergy.com/research/the-passive-investment-boom-and-its-consequences
217 https://www.esrb.europa.eu/pub/pdf/asc/esrb.asc190617_9_canetfscontributesystemicrisk~983ea11870.en.pdf
218 https://macrosynergy.com/research/the-dangers-of-leveraged-etfs
219 https://macrosynergy.com/research/the-idea-of-uncovered-equity-parity
220 https://www.sciencedirect.com/science/article/abs/pii/S0275531917304580
221 https://macrosynergy.com/research/liquidity-events
222 https://macrosynergy.com/research/high-speed-trading-lessons-from-quantum-physics
223 https://macrosynergy.com/research/how-fed-asset-purchases-reduce-yield-term-premia
224 https://macrosynergy.com/research/the-dangers-of-ultra-low-interest-rates-in-europe
225 https://macrosynergy.com/research/why-and-when-equity-duration-matters
226 https://macrosynergy.com/research/europes-financial-transaction-tax-and-the-consequences
227 https://macrosynergy.com/research/chinas-commodity-financing-deals
228 https://macrosynergy.com/research/explaining-fx-forward-bias
229 https://macrosynergy.com/research/the-limited-effect-of-fx-interventions
230 https://macrosynergy.com/research/understanding-duration-feedback-loops
231 https://macrosynergy.com/research/setback-risk
232 https://www.systemicrisk.ac.uk/endogenous-risk
233 https://macrosynergy.com/research/fx-carry-trade-crashes
234 https://macrosynergy.com/research/momentum-trading-and-setback-risk
235 https://macrosynergy.com/research/a-theory-of-hedge-fund-runs
236 https://macrosynergy.com/research/volatility-of-term-premia-at-the-zero-lower-bound
237 https://macrosynergy.com/research/understanding-market-beta-in-fx
238 https://macrosynergy.com/research/estimating-the-positioning-of-trend-followers
239 https://macrosynergy.com/research/crowded-trades
240 https://macrosynergy.com/research/reported-economic-changes-and-the-treasury-market-impact-and-payback
241 https://macrosynergy.com/research/quantitative-easing-and-var-shocks
242 https://macrosynergy.com/research/some-stylized-facts-of-fx-liquidity
243 https://macrosynergy.com/research/understanding-global-liquidity
244 https://macrosynergy.com/research/the-1x1-of-risk-perception-measures
245 https://macrosynergy.com/research/what-variance-swaps-tell-us-about-risk-premia
246 https://macrosynergy.com/research/vix-term-structure-as-a-trading-signal
247 https://macrosynergy.com/research/tracking-investor-expectations-with-etf-data
248 https://macrosynergy.com/research/when-economic-data-surprises-matter-most
249 https://macrosynergy.com/research/why-decision-makers-are-unprepared-for-crises
250 https://macrosynergy.com/research/the-power-and-origin-of-uncertainty-shocks
251 https://macrosynergy.com/research/measures-of-risk-and-uncertainty
252 https://macrosynergy.com/research/volatility-surprises
253 https://macrosynergy.com/research/the-dangerous-disregard-of-fat-tails-in-quantitative-finance
254 https://macrosynergy.com/research/modelling-the-relation-between-volatility-and-returns

6. How to establish a proof of concept for a macro trading strategy

1 *https://macrosynergy.com/research/how-to-build-a-macro-trading-strategy-with-open-source-python*
2 *https://macrosynergy.com/research/macroeconomic-cycles-and-asset-class-returns*
3 *https://macrosynergy.com/research/pure-macro-fx-strategies-the-benefits-of-double-diversification*
4 *https://pandas.pydata.org*
5 *https://matplotlib.org*
6 *https://scikit-learn.org/stable*
7 *https://docs.macrosynergy.com/stable/index.html*
8 *https://github.com/macrosynergy/macrosynergy*
9 *https://docs.macrosynergy.com/stable/index.html*
10 *https://macrosynergy.com/research/how-macro-quantamental-trading-signals-will-transform-asset-management*
11 *Chapter 4: The J.P. Morgan Macrosynergy Quantamental System*
12 *https://macrosynergy.com/academy/quantamental-indicators-on-jpmaqs*
13 *https://macrosynergy.com/academy/notebooks/economic-trends*
14 *https://macrosynergy.com/academy/notebooks/manufacturing-confidence-scores*
15 *https://macrosynergy.com/academy/quantamental-indicators-on-jpmaqs*
16 *https://docs.macrosynergy.com/stable/macrosynergy.download.html*
17 *https://docs.macrosynergy.com/stable/macrosynergy.download.jpmaqs.html*
18 *https://docs.macrosynergy.com/stable/macrosynergy.download.jpmaqs.html*
19 *https://macrosynergy.com/academy*
20 *https://macrosynergy.com/academy/notebooks/trading-strategies-with-jpmaqs*
21 *https://docs.macrosynergy.com/stable/macrosynergy.panel.view_ranges.html*
22 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*
23 *https://docs.macrosynergy.com/stable/macrosynergy.panel.view_timelines.html*
24 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*
25 *https://macrosynergy.com/research/macro-information-changes*
26 *https://docs.macrosynergy.com/stable/macrosynergy.panel.view_correlations.html*
27 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*
28 *https://docs.macrosynergy.com/stable/macrosynergy.panel.panel_calculator.html*
29 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*
30 *https://docs.macrosynergy.com/stable/macrosynergy.panel.make_zn_scores.html*
31 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*
32 *https://docs.macrosynergy.com/stable/macrosynergy.panel.make_relative_value.html*
33 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*
34 *https://docs.macrosynergy.com/stable/macrosynergy.panel.panel_calculator.html*
35 *https://docs.macrosynergy.com/stable/macrosynergy.panel.make_zn_scores.html*
36 *https://docs.macrosynergy.com/stable/macrosynergy.panel.linear_composite.html*
37 *https://macrosynergy.com/research/optimal-signals*
38 *https://docs.macrosynergy.com/stable/macrosynergy.learning.sequential.signal_optimizer.html*

39 *https://docs.macrosynergy.com/stable/macrosynergy.learning.sequential.signal_optimizer.html*
40 *https://macrosynergy.com/research/fx-trading-signals-with-regression-based-learning*
41 *https://macrosynergy.com/research/how-to-adjust-regression-based-trading-signals-for-reliability*
42 *https://macrosynergy.com/research/using-principal-components-to-construct-macro-trading-signals*
43 *https://macrosynergy.com/research/regression-signals*
44 *https://macrosynergy.com/research/evaluating-macro-trading-signals-in-three-simple-steps*
45 *https://macrosynergy.com/research/testing-macro-trading-factors*
46 *https://docs.macrosynergy.com/stable/macrosynergy.panel.category_relations.html*
47 *https://docs.macrosynergy.com/stable/macrosynergy.panel.category_relations.html*
48 *https://docs.macrosynergy.com/stable/macrosynergy.visuals.multiple_reg_scatter.html*
49 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*
50 *https://docs.macrosynergy.com/stable/macrosynergy.signal.signal_return_relations.html*
51 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*
52 *https://docs.macrosynergy.com/stable/macrosynergy.pnl.naive_pnl.html*
53 *https://docs.macrosynergy.com/stable/macrosynergy.pnl.naive_pnl.html*
54 *https://macrosynergy.com/academy/notebooks/introduction-to-macrosynergy-package*

Part 2

7. Examples of macro trading factors

1 *https://macrosynergy.com/academy/examples-macro-trading-factors*
2 *https://macrosynergy.com/research/macroeconomic-cycles-and-asset-class-returns*
3 *https://macrosynergy.com/academy/notebooks/macroeconomic-cycles-and-asset-class-returns*
4 *https://macrosynergy.com/research/considering-rational-inattention-for-trading-strategies*
5 *https://macrosynergy.com/academy/notebooks/intuitive-gdp-growth-estimates*
6 *https://macrosynergy.com/academy/notebooks/demographic-trends*
7 *https://macrosynergy.com/academy/notebooks/labor-market-dynamics*
8 *https://macrosynergy.com/academy/notebooks/labor-market-tightness*
9 *https://macrosynergy.com/academy/notebooks/consumer-price-inflation-trends*
10 *https://macrosynergy.com/academy/notebooks/inflation-targets*
11 *https://macrosynergy.com/academy/notebooks/equity-index-future-returns*
12 *https://macrosynergy.com/research/testing-macro-trading-factors*
13 *https://macrosynergy.com/academy/notebooks/fx-forward-returns*
14 *https://macrosynergy.com/academy/notebooks/duration-returns*
15 *https://macrosynergy.com/research/macro-information-changes*
16 *https://macrosynergy.com/academy/notebooks/macro-information-changes-and-fixed-income*
17 *https://macrosynergy.com/research/reported-economic-changes-and-the-treasury-market-impact-and-payback*
18 *https://macrosynergy.com/academy/notebooks/intuitive-gdp-growth-estimates*
19 *https://macrosynergy.com/academy/notebooks/technical-gdp-growth-estimates*

20 https://macrosynergy.com/academy/notebooks/industrial-production-trends

21 https://macrosynergy.com/academy/notebooks/private-consumption

22 https://macrosynergy.com/academy/notebooks/private-consumption

23 https://macrosynergy.com/academy/notebooks/foreign-trade-trends

24 https://macrosynergy.com/academy/notebooks/manufacturing-confidence-scores

25 https://macrosynergy.com/academy/notebooks/services-confidence-scores

26 https://macrosynergy.com/academy/notebooks/construction-activity

27 https://macrosynergy.com/academy/notebooks/private-consumption

28 https://macrosynergy.com/academy/notebooks/labor-market-tightness

29 https://macrosynergy.com/academy/notebooks/labor-market-dynamics

30 https://macrosynergy.com/academy/notebooks/consumer-price-inflation-trends

31 https://macrosynergy.com/academy/notebooks/consumer-price-inflation-trends

32 https://macrosynergy.com/academy/notebooks/producer-price-inflation

33 https://macrosynergy.com/academy/notebooks/private-credit-expansion

34 https://macrosynergy.com/academy/notebooks/monetary-aggregates

35 https://macrosynergy.com/academy/notebooks/monetary-aggregates

36 https://macrosynergy.com/academy/notebooks/international-investment-position

37 https://macrosynergy.com/academy/notebooks/international-investment-position

38 https://macrosynergy.com/research/macro-efficiency

39 https://macrosynergy.com/research/regression-signals

40 https://macrosynergy.com/academy/notebooks/shares-in-global-production

41 https://macrosynergy.com/research/evaluating-macro-trading-signals-in-three-simple-steps

42 https://macrosynergy.com/research/testing-macro-trading-factors

43 https://macrosynergy.com/academy/examples-macro-trading-factors

44 https://macrosynergy.com/research/equity-versus-fixed-income-the-predictive-power-of-bank-surveys

45 https://macrosynergy.com/research/macroeconomic-cycles-and-asset-class-returns

46 https://macrosynergy.com/research/excess-inflation-and-asset-class-returns

47 https://macrosynergy.com/research/intervention-liquidity

48 https://macrosynergy.com/research/macro-factors-for-the-risk-parity-trade

49 https://macrosynergy.com/research/cross-country-equity-futures-strategies

50 https://macrosynergy.com/research/statistical-learning-for-sectoral-equity-allocation

51 https://macrosynergy.com/research/macro-factors-and-sectoral-equity-allocation

52 https://macrosynergy.com/research/macro-trends-and-equity-allocation-a-brief-introduction

53 https://macrosynergy.com/research/equity-trend-following-and-macro-headwinds

54 https://macrosynergy.com/research/inflation-and-equity-markets

55 https://macrosynergy.com/research/equity-consumption

56 https://macrosynergy.com/research/jobs-growth-as-trading-signal

57 https://macrosynergy.com/research/macro-information-changes

58 https://macrosynergy.com/research/macro-demand-based-rates-strategies

59 https://macrosynergy.com/research/merchandise-import-as-predictor-of-duration-returns

60 https://macrosynergy.com/research/fiscal-policy-criteria-for-fixed-income-allocation

61 https://macrosynergy.com/research/the-predictive-power-of-real-government-bond-yields

62 https://macrosynergy.com/research/trend-following-combining-market-and-macro-information

63 https://macrosynergy.com/research/the-power-of-macro-trends-in-rates-markets

64 https://macrosynergy.com/research/inflation-expectations-and-interest-rate-swap-returns

65 https://macrosynergy.com/research/duration-volatility-risk-premia

66 https://macrosynergy.com/research/advanced-fx-carry-strategies-with-valuation-adjustment

67 https://macrosynergy.com/research/fx-trading-signals-with-regression-based-learning

68 https://macrosynergy.com/research/fx-trading-signals-common-sense-and-machine-learning

69 https://macrosynergy.com/research/fx-and-macro-headwinds

70 https://macrosynergy.com/research/pure-macro-fx-strategies-the-benefits-of-double-diversification

71 https://macrosynergy.com/research/modified-and-balanced-fx-carry

72 https://macrosynergy.com/research/how-to-use-fx-carry-in-trading-strategies

73 https://macrosynergy.com/research/economic-growth-and-fx-forward-returns

74 https://macrosynergy.com/research/inventory-scores-and-metal-futures-returns

75 https://macrosynergy.com/research/business-sentiment-and-commodity-future-returns

76 https://macrosynergy.com/research/commodity-carry-as-a-trading-signal-part-1

77 https://macrosynergy.com/research/commodity-carry-as-a-trading-signal-part-2

78 https://macrosynergy.com/research/predicting-base-metal-futures-returns-with-economic-data

79 https://macrosynergy.com/research/sovereign-debt-sustainability-and-cds-returns

8. Data science and macro trading factors

1 https://docs.macrosynergy.com/stable/index.html

2 https://macrosynergy.com/research/fx-trading-signals-with-regression-based-learning

3 https://macrosynergy.com/research/statistical-learning-for-sectoral-equity-allocation

4 https://macrosynergy.com/academy/statistics-packages-with-quantamental-indicators

5 https://macrosynergy.com/research/fx-trading-signals-with-regression-based-learning

6 https://macrosynergy.com/academy/notebooks/regression-based-fx-signals

7 https://macrosynergy.com/research/regression-signals

8 https://macrosynergy.com/academy/notebooks/fx-forward-returns

9 https://macrosynergy.com/research/considering-rational-inattention-for-trading-strategies

10 https://macrosynergy.com/academy/notebooks/intuitive-gdp-growth-estimates

11 https://macrosynergy.com/academy/notebooks/manufacturing-confidence-scores

12 https://macrosynergy.com/academy/notebooks/labor-market-dynamics

13 https://macrosynergy.com/academy/notebooks/consistent-core-cpi-trends

14 https://macrosynergy.com/academy/notebooks/inflation-targets

15 https://macrosynergy.com/academy/notebooks/producer-price-inflation

16 https://macrosynergy.com/academy/notebooks/inflation-expectations

17 https://macrosynergy.com/academy/notebooks/real-interest-rates

18 https://macrosynergy.com/academy/notebooks/international-investment-position

19 https://macrosynergy.com/academy/notebooks/terms-of-trade

20 https://macrosynergy.com/academy/notebooks/regression-based-fx-signals

21 https://macrosynergy.com/research/optimal-signals

22 https://docs.macrosynergy.com/stable/macrosynergy.learning.splitters.html

23 https://docs.macrosynergy.com/stable/macrosynergy.learning.sequential.html

24 https://macrosynergy.com/academy/notebooks/regression-based-fx-signals

25 https://macrosynergy.com/research/testing-macro-trading-factors

26 https://macrosynergy.com/research/statistical-learning-for-sectoral-equity-allocation

27 https://macrosynergy.com/academy/notebooks/sectoral-equity-indicators

28 https://macrosynergy.com/academy/notebooks/statistical-learning-for-sectoral-equity-allocation

29 https://macrosynergy.com/research/macro-trends-and-equity-allocation-a-brief-introduction

30 https://macrosynergy.com/research/macro-factors-and-sectoral-equity-allocation

31 https://macrosynergy.com/research/macro-factors-and-sectoral-equity-allocation

32 https://macrosynergy.com/academy/notebooks/sectoral-equity-index-returns

33 https://macrosynergy.com/research/macro-factors-and-sectoral-equity-allocation

34 https://macrosynergy.com/research/optimal-signals

35 https://macrosynergy.com/research/regression-signals

36 https://macrosynergy.com/academy/notebooks/sectoral-equity-index-returns

37 https://docs.macrosynergy.com/stable/macrosynergy.learning.preprocessing.html

38 https://macrosynergy.com/research/regression-signals

39 https://docs.macrosynergy.com/stable/macrosynergy.learning.forecasting.html

40 https://docs.macrosynergy.com/stable/macrosynergy.learning.forecasting.html

41 https://docs.macrosynergy.com/stable/macrosynergy.learning.forecasting.html

42 https://macrosynergy.com/research/how-to-adjust-regression-based-trading-signals-for-reliability

43 https://macrosynergy.com/research/optimal-signals

44 https://docs.macrosynergy.com/stable/macrosynergy.learning.splitters.html

45 https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.TimeSeriesSplit.html

46 https://docs.macrosynergy.com/stable/macrosynergy.learning.model_evaluation.metrics.metrics.html

47 https://docs.macrosynergy.com/stable/macrosynergy.learning.sequential.html

48 https://macrosynergy.com/research/evaluating-macro-trading-signals-in-three-simple-steps

49 https://macrosynergy.com/research/testing-macro-trading-factors

50 https://docs.macrosynergy.com/stable/macrosynergy.panel.category_relations.html

51 https://docs.macrosynergy.com/stable/macrosynergy.panel.category_relations.html

52 https://macrosynergy.com/research/macro-factors-and-sectoral-equity-allocation

53 https://macrosynergy.com/research/fx-trading-signals-with-regression-based-learning

54 https://macrosynergy.com/research/statistical-learning-for-sectoral-equity-allocation

55 https://macrosynergy.com/research/optimal-signals

56 https://macrosynergy.com/research/regression-signals

57 https://macrosynergy.com/research/using-principal-components-to-construct-macro-trading-signals

58 https://macrosynergy.com/research/how-beta-learning-improves-macro-trading-strategies

59 https://macrosynergy.com/research/how-to-adjust-regression-based-trading-signals-for-reliability

60 https://macrosynergy.com/research/how-random-forests-can-improve-macro-trading-signals

Index

CONTENTS