Alternative Investment Analyst Review

CEO's Letter

As the calendar turns to 2014, we are reminded that the only constant in life is change. That is certainly true in the alternative investment space where new products, wrappers, and a multitude of economic variables continue to underscore the need for a perpetual commitment to education. The Alternative Investment Analyst Review will always seek to play an important role in this quest for our Members and their clients.

This is also a year of change at the top of the CAIA house. Florence Lombard, who has been a founder, board member, and leader of CAIA since our humble beginnings in 2002, announced her retirement over a year ago. Practicing what we preach, the search process was thoughtful and thorough, with a lean toward finding a successor who could bring some "uncorrelated" skills into the CAIA fold. I hope to live up to that credo in everything I do. I thank Florence for her leadership, vision and voice; our organization and our industry are in a better place as a result of those efforts.

In the coming months and quarters, I hope to get out and meet many of you at local chapter events or through our affiliations with our association and academic partners. I will promise to never lose sight of the fact that I work for you, our members, and your experience and expectations must shape, focus and evolve our mission to be a leader in alternative investment education.

The current issue of AIAR contains a little something for everyone. There are five articles covering a very broad range of topics. In the first article we cover non-traded REITs as an alternative asset class and the characteristics of its distinct risk-return profile. This is followed by a broad review of the current economic research on the structure and function of the world oil market. Our regulators always remain top-of-mind, and our third article updates us on the impact of recent regulatory changes on UCITS CTAs. We also take a closer look at the US futures industry as a variety of participants go there seeking to manage a multitude of risk. Staying with that risk theme, the final section of this issue discusses a "Momentum Monitor", which is a tool to assist risk takers and investment managers in their overall risk management process. The Momentum Monitor is produced by Alex Ineichen, CAIA, and will be a regular feature of AIAR going forward.

I wish all of you a healthy and prosperous 2014. As always, we encourage your feedback, suggestions for future content, and direct submissions from our Members. Your opinions matter to us.

Bill Kelly, CEO
Chartered Alternative Investment Analyst Association

Call for Articles

Article submissions for future issues of *Alternative Investment Analyst Review* are always welcome. Articles should be approximately 15 pages, single-spaced, and cover a topic of interest to CAIA members. Additional information on submissions can be found at the end of this issue. Please email your submission or any questions to **AIAR@CAIA.org**.

Chosen pieces will be featured in future issues of AIAR, archived on **CAIA.org**, and promoted throughout the CAIA community.

Table of Contents

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The analysis reveals that the extent to which daily data are co-integrated provides a good indicator of the profitability of the high-frequency pairs trading. For each series, the in-sample information ratio is a good indicator of the future profitability as well.

The results show that a statistical arbitrage opportunity exists when applying a novel diversified pair trading strategy to high-frequency data. In particular, even once very conservative transaction costs are taken into account, the suggested trading portfolio achieves attractive information ratios (e.g., above 3 for an average pair sampled at the high-frequency interval and above 1 for a daily sampling frequency).

Perspectives

ABSTRACT: This article demonstrates how U.S. futures markets were "forged by … [decades of] of trial and error [efforts] … and … were not the product of some designing intelligence." These markets "represent a distillation of what human experience has found" to work. In an era of optimistic proposals to fundamentally redesign market structures, it may be useful for participants of mature financial centers to be reminded of these historical facts. In addition, participants from new emerging financial centers, who are "crossing the river by feeling the stones," may also find it useful to understand how U.S. futures markets evolved in a trial-and-error fashion, overcoming adversity through innovation each step of the way.

In demonstrating the trial-and-error development of futures markets, this article will briefly cover how and why modern futures trading started in Chicago; how the Chicago and New York futures exchanges have had to constantly innovate in order to remain in business, including with speculative product launches, demutualization, and the development of electronic trading; and why some futures contracts fail. After reviewing the history of U.S. futures markets, one does get a sense of the resiliency of these institutions, in constantly responding to adversity, from their earliest days through well into the present.

Momentum Monitor

ABSTRACT: Risk is often defined as exposure to change. Spotting change, therefore, is important. There are essentially three approaches to change: 1. Displaying complete ignorance, 2. Having a wild guess as to what it means, or 3. Measuring it in a systematic fashion with an applicable methodology and adapting to it. The author recommends choice number 3.

Momentum can be perceived as a philosophy. The author discusses the Momentum Monitor (MOM) and recommends it as a risk management tool. If risk is defined as "exposure to change," then one ought to spot the change.

The Case for Investing in Non-Traded REITs

Sameer Jain
Chief Economist and Managing Director, American Realty Capital

1. Introduction

Non-traded REITs (NTRs), like their publicly traded counterparts, make investments in income-producing commercial real estate. They typically hold multiple properties in a single portfolio and are ordinarily categorized by the types of properties they own, such as retail, industrial, multifamily, office, and storage, among others. Certain of these REITs structure their underlying investments as net leases in which the tenant is responsible for bearing real estate costs directly, such as property taxes, insurance, operating expenses, and capital items, in addition to rent and utility payments. By distributing essentially 100% of all rent payments received by tenants, these REITs provide a durable stream of monthly income to their investors and also offer the potential for long-term capital appreciation through property value growth.

The term private REIT commonly attached to NTRs is a misnomer, as these REITs are publicly registered and are thus subject to many of the same public reporting, tax qualification, SEC regulation, and governance requirements that an exchange-traded public REIT must meet. Unlike traded public REITs, these vehicles are not susceptible to exchange-traded supply and demand-driven price volatility. Rather, price discovery happens through periodic valuations, much as in private equity real estate investing. NTRs generally provide little or no interim liquidity and usually have a five to seven-year lifespan. However, unlike public REITs, NTRs are only available to investors that meet established net worth and income standards. With interest rates at rock-bottom levels, safe yet high-yielding assets remain scarce. Investing in NTR offers these advantages:

- Potential for superior risk-adjusted returns.
- Higher dividends than traded REITs.
- Avoiding the potential inflated valuations in the traded REIT sector.
- Illiquidity premium that can be captured by the long-term investor.
- Ability to raise and invest capital at opportune times in the market cycle.
- Valuations that are not subject to public market volatility.

NTRs have started to attract considerable investor interest. We estimate that around 70 NTRs have raised and invested $80 billion to $90 billion in equity during the past decade, with about $10 billion raised and deployed annually in recent years. The industry is heavily concentrated, with the top 10 NTRs controlling a dominant share.

2. Determining Value

Publicly-held companies typically trade at a multiple of price to earnings (or in the case of REITs, price to funds from operations). Unlike traded REITs, where value is tied to the price at which shares trade on an exchange and is often influenced by emotions (such as fear and greed) that drive public markets, shareholders of NTRs see value equal to the cost of the asset at the time of purchase. Thereafter, the property is subsequently revalued according to conventional real estate valuation methodologies, including comparable sales analysis, discounted cash flow analysis and replacement cost analysis. Moreover, NTRs are largely insulated from broader exchange-traded fluctuations as their net asset value, not market sentiment, drives pricing.

Exchange-listed REITs commonly trade at modest premiums to NAV (largely due to the liquidity they offer); the mean premium since 1990 has been around 3%. However, there are periods when public markets are grossly overvalued and this premium may rise to double digits. Mean reversion is a generally consistent force within financial markets (albeit difficult to time). Therefore, overvalued traded REIT prices eventually revert to the historic lower mean.

3. Risk-Adjusted Returns

Traded public REITS are subject to market risk through trading volatility. NTRs may not be subject to the same risk. Prices of traded REITs may change in reaction to changes in equity markets, not because of their fundamental exposures to systematic equity risk, but because of the buying and selling pressures resulting from broad portfolio adjustments by managers. To the degree that correlations between prices of traded REITs and broad equity markets do not reflect the systematic risk of this asset class, the required return on NTRs should contain a lower equity risk premium, which will make NTRs more attractive. The historic equity risk premium over long periods of time is around 4%. This suggests that someone investing in publicly-traded REITs ought to expect 4% greater returns for doing exactly the same thing in NTRs. Thus, assuming rational investors should demand higher returns from investing in securities with higher risk, to match a 6% return on a NTR a traded public REIT must have a return of 10% (6%

plus 4% market risk premium). This suggests that given the exact same underlying investment (in property or in any other asset), the expected return for holding it in a publicly-traded structure as opposed to a non-traded structure ought to be at least 4% higher.

Of course, the illiquidity of the NTRs is a double-edged sword. While this may lead to a reduction in the equity premium demanded by investors for investing in NTRs, it could lead them to demand a higher expected return in order to compensate them for NTRs' lack of liquidity. As discussed below, not all investors are equally averse to illiquidity, and, therefore, they may demand different premiums for investing in illiquid assets.

4. Liquidity Preferences Differ

Liquidity is measured by the ability to convert a security quickly into cash without any price discount. Traded REITs provide liquidity by virtue of trading on public stock exchanges. Again, NTRs are not traded on exchanges. Instead, limited liquidity for some NTRs is available through interim redemption programs such as tender offers with a full cycle liquidity exit event projected or attempted within five to seven years of program inception.

Liquidity preferences differ based on the investor's expected holding period. For the short-term speculator, the liquidity afforded by traded REITs is essential. However, for the long-term investor interested in unlocking the long-term illiquidity premium following a buy-and-hold strategy, the liquidity offered by a traded REIT is of little benefit, for they arguably have no need for it. Moreover, liquidity can exaggerate losses for publicly traded REIT investors. For example, if enough investors flee a traded public REIT, the share price can drop below the value of the underlying real estate. The loss floor on a NTR investment by contrast is moderated by the inability of investors to panic sell their securities. This suggests long-term investors, for the reasons outlined above, may derive unique benefits from owning real estate in NTR formats rather than in traded REIT structures. Though long-term investors may demand a relatively small premium for the illiquidity of NTRs, these investments will need to offer a premium to compensate the long-term investors for illiquidity risk.

5. Capital-Raising Cycle

Traded REITs are subject to market movements and market volatility in their ability to raise capital. Generally, traded REITs have difficulty attracting capital when the real estate sector is out of favor (i.e., prices are low) or when there is a general perception of greater opportunities available elsewhere. They have typically raised and invested capital when real estate markets were in favor and capital markets activity buoyant—a time when property prices are also generally at their highest. NTRs, by comparison, cater to long-term investors who are usually agnostic to cyclical activity of capital markets and are seeking superior risk-adjusted yields with low

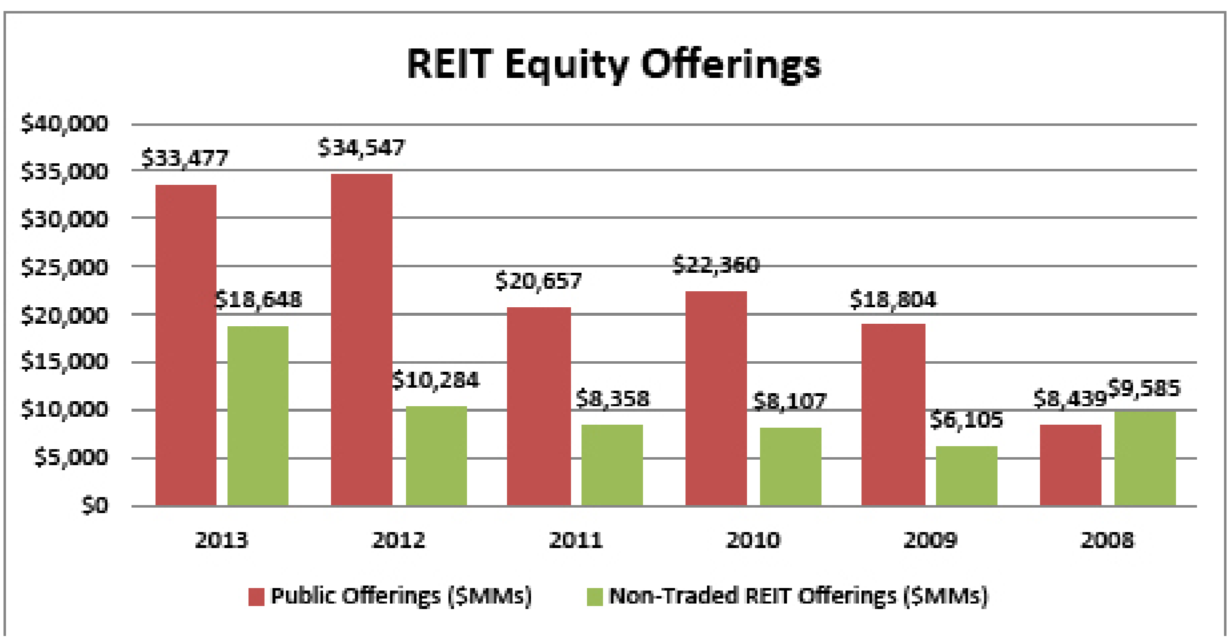

Exhibit 1 REIT Equity Offerings Source: SNL Financial

traded market correlations. This suggests traded REITs, unlike NTRs, are generally unable to raise and invest capital at times when it is most opportune to do so.

6. Managing for the Long-Term

Traded REITs must contend with the demands of analysts and speculative investors. The pressure to meet and beat analysts' forecasts, where missing earnings expectations may lead to significant stock price declines, often prompts management to focus on short-term quarterly earnings. Consequently, resources better spent on developing, acquiring, and managing properties are employed to manage earnings and meet short-term market expectations. By contrast, and to the betterment of the portfolio, NTR managers are afforded the advantage of concentrating on longer-term real estate investing opportunities because their investors share a common long-term return objective. In short, traded REITs must contend with the pressures for quarterly performance inherent within the exchange-traded market. Yet such quarterly measurement is often a mismatch with the investment characteristics of real estate as an asset class. The absence of this pressure in the private markets suggests managers of NTRs are typically more readily able to focus long term on real estate investment and meeting investors' long-term investment objectives, rather than managing quarterly earnings expectations.

7. Conclusion

NTRs typically invest in sector-specific real estate programs, targeting stable, fully occupied properties subject to long-term leases to strong credit tenants. They are thus able to generate immediate, durable, rent-driven cash flows from the inception of the investment as capital is deployed without a cash drag. Much like traditional private equity core real estate investing, they aggregate property through acquisitions and build diversified portfolios by tenant, geography, industry, and lease duration. They return value from these aggregated portfolios via asset sales, public listings, or mergers, usually over a five to seven-year timeframe. In the current environment, they afford a way to make more tactical investing calls because they allow investors to profit from the current historic high spread between low cost financing and high acquisition cap rates.

NTRs may hold a number of investment advantages over their publicly traded counterparts: notably, a valuation of shares reflecting the intrinsic underlying value of owned real estate, favorable risk-adjusted returns, appropriate liquidity characteristics for long-term investors, superior capital-raising and deployment dynamics, and a heightened management focus on maximizing long-term investment opportunities.

Endnotes

Of course, some of the factors that affect public markets could eventually affect the net asset values of NTRs. For evidence on the size of illiquidity premium see Khandani and Lo (2009), "Illiquidity Premia in Asset Returns: An Empirical Analysis of Hedge Funds, Mutual Funds and U.S. Equity Portfolios," http://web.mit.edu/Alo/www/Papers/liquidity4.pdf

Author Bio

Sameer Jain has executive management cross-functional responsibilities at American Realty Capital, including heading risk management, firm strategy, and

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Oil Price Drivers and Movements:

The Challenge for Future Research

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1. Introduction

The complexity of the world oil market has increased dramatically in recent years and new approaches are needed to understand, model, and forecast oil prices today. In addition to the commencement of the financialization era in oil markets, there have been structural changes in the global oil market. Financial instruments are communicating information about future conditions much more rapidly than in the past. Prices from long and short-duration contracts have started moving more together. Abrupt changes in supply and demand, influnced by events and trends, including the financial crisis of 2008-09, increases in China's economic growth rate, the Libyan uprising, the Iranian Nuclear standstill, and the Deepwater Horizon oil spill change expectations and current prices. Although volatility appears greater over this period, financialization makes price discovery more robust. Most empirical economic studies suggest that fundamental factors shaped the expectations over 2004-08, although financial bubbles may have emerged just prior to and during the summer of 2008.

With increased price volatility, major exporters are considering ways to achieve more price stability to improve long-term production and consumption decisions. Managing excess capacity has historically been an important method for keeping world crude oil prices stable during periods of sharp supply or demand shifts. Building and maintaining excess capacity in current markets allows greater price stability when Asian economic growth accelerates suddenly or during periods of supply uncertainty in major oil producing regions. OPEC can contribute to price stability more easily when members agree on the best use of oil production capacity.

Important structural changes have emerged in the global oil market after major price increases. Partially motivated by governments' policies, major developments in energy and oil efficiencies occurred after the oil price increases of the early and the late 1970s, such as improvements in vehicle fuel efficiency, building codes, power grids, and energy systems. On the supply side, seismic imaging and horizontal drilling, as well as favorable tax regimes, expanded production capacity in countries outside OPEC. After the oil price increases of 2004-08, investments in oil sands, deep water, biofuels, and other non-conventional sources of energy accelerated. Recent improvements in shale gas production could well be transferred to oil-producing activities, resulting in expanded oil supplies in areas that were previously considered prohibitively expensive. The search for alternative transportation fuels continues with expanded research into compressed natural gas, biofuels, diesel made from natural gas, and electric vehicles.

In spite of these advances, some aspects of the world oil market are not well understood. Despite numerous attempts to model the behavior of OPEC and its members, there exists no credible, verifiable theory about the behavior of this 50 year-old organization. OPEC has not acted like a monolithic cartel, constraining supplies to raise prices. Empirical evidence suggests that at some times, members coordinate supply responses and at other times they compete with each other. Supply-restraint strategies include slower capacity expansions, as well as curtailed production from existing capacity. Regional political considerations and broader economic goals beyond oil are influential factors in a country's oil decisions. Furthermore, the economies and financial needs of OPEC members have changed dramatically since the 1970s and 1980s.

This review represents a broad survey of economic research and literature related to the structure and functioning of the world oil market. The theories and models of oil demand and supply reviewed here, although imperfect in many respects, offer a clear and well-defined perspective on the forces that are shaping the markets for crude oil and refined products. Much work remains to be done if we are to achieve a more complete understanding of these forces and the trends that lie ahead. The contents that follow represent an assessment of how far we have come and where we are headed. Around the world governments, busineses and consumers share a vital interest in the benefits that flow from an efficient, well-functioning oil market. It is hoped, therefore, that the discussion in this review will find a broad audience.

2. Price Volatility and Uncertain Conditions

Oil prices have fluctuated widely since 2004. Brent crude oil prices rose from $29 to $38 per barrel (annual averages) between 2003 and 2004. They rose steadily until 2008, reaching a record near $147 per barrel in July 2008. This price spike reflected extremely strong Asian economic growth, combined with certain geopolitical events. Prices collapsed below $33 within the next few months as the world economy spun downward into financial disarray. They spurted back to levels above $80 per barrel in 2010, as the economies in Asia and elsewhere recovered. Additional price increases in 2011 beyond $100 per barrel were prompted by continued Asian growth and supply uncertainty mounted with the Arab uprising and the Libyan disruption. Continued fears about the financial system and future economic growth lingered in August 2011, causing world oil prices to begin their retreat once again.

These conditions have created massive uncertainty about where future oil prices will be headed and what factors create these dramatic price movements. Peak oil arguments abound during an era when non-OPEC oil production has increased only modestly despite the record-high prices. Turmoil dominates the political landscape in the Middle East, fueling additional concerns about the security of oil supplies. Most disconcerting to both oil producing and oil-consuming nations has been the financialization of oil, where financial motives and trading permeate oil transactions and make physical markets appear less important.

This uncertainty creates very significant problems for major oil-consuming countries that are trying to recover from financial disintegration, as well as investors who are considering long-term allocations to commodities. It also raises important concerns for major oil-producing countries with ample resources. Should they expand capacity to supply growing economies and at what rate? How much spare oil capacity should be maintained to offset sudden oil-market surprises—unexpectedly higher economic growth, political unrest in oil-producing regions, or major oil spills in offshore drilling areas? Fundamental factors should be important for both capacity decisions, but these uncertainties have eroded the belief that these factors still operate in the same way that they have in the past.

Capacity expansion influences both short and long-term market operations. First, greater capacity allows more future production to meet growing demand. These decisions require an understanding of long-term market conditions. Second, additional capacity can also build surplus capacity for market imbalances. These decisions require an understanding of short-term market conditions. Although the distinction between the short and long term can be ambiguous, we define the short-term to include horizons of three years or less.

Oil markets are not easy to understand and projections of future oil prices have not been accurate consistently. If fundamental supply and demand analysis and oil market modeling have any benefits, it would appear to be in their ability to organize complex information efficiently and to provide better understanding of how oil markets perform. For this reason, it is sensible to emphasize these characteristics, rather than to focus on their suitability for forecasting.

3. Long-Run Oil Price Drivers and Models

Oil represents a substantial proportion of global energy demand. As the world's most highly traded international commodity, oil will continue to play a large role in meeting energy demand in the future. Over the long run, the price of oil will be influenced by four major trends: (1) global economic growth, (2) demand-side technological progress and efficiency gains, (3) new alternative energy sources, and (4) the changing costs of production. The depletion of easily extracted resources is pushing production into more technologically demanding fields, lower-quality crudes, and higher-cost operating environments. At the same time, dramatic improvements in technology are expected to continue to reduce the cost of finding and producing oil from such reserves. Government policies will have important impacts on the costs of both petroleum products and competitive energy sources. Understanding how production, consumption, and the price of oil will change over the coming decades is of vital interest to both oil-producing and oil-consuming nations, with strong implications for energy policy, economic growth, climate-change policy, and international stability.

3.1. Oil Demand: Drivers and Trends

Generally speaking, when the world economy as a whole experiences growth, oil demand will increase. The existence of this fundamental relationship is uncontested, but its strength varies between regions and will be moderated by many factors with the potential to curb demand, such as fuel-saving technologies, fuel-switching to different forms of primary energy, and policies designed to constrain carbon dioxide emissions.

Much of the recent growth in global oil consumption (which rose by 1.5% per year between 1985 and 2008) occurred outside the OECD nations. As a percent of world consumption, the emerging nations' share has grown from 37.6% to 44.5% over this period.

Developing economies are expected to continue being the primary drivers of the growth in global oil demand. The hypothesized energy and environmental Kuznets curve, which views investments in energy efficiency as a luxury good that become more affordable and widespread as developing economies mature and prosper, teaches us that continued strong economic growth in China and elsewhere may work paradoxically to restrain the growth rate of demand—if only in the longer run.

3.1.1. Growth and Industrialization

Per-capita oil demand grows at the same rate as the economy in many emerging economies, so long as other factors like prices do not change. Many countries are experiencing rapid increases in vehicle penetration and ownership rates as incomes rise. Based on estimates as of 1973, oil income elasticities exceeded unity throughout the developing regions of the world, and approached a level of 2 in the poorest nations. This implies that oil demand should increase at least as fast as GDP in the developing world, holding constant energy prices and technological progress. In the poorest Asian nations, oil demand should expand nearly twice as fast as GDP (Medlock and Soligo 2001 and Van Benthem and Romani 2009).

In contrast, per-capita oil demand grows more slowly than GDP within the OECD, even before the impact of potentially rising prices is factored in. Vehicle ownership per person has stabilized and consumers are beginning to purchase alternative-fuel vehicles in these countries. Gately and Huntington (2002) estimate that the long-run income elasticity to be 0.55 in the more mature OECD countries, implying that oil demand may increase only about half as fast as GDP in the industrialized portions of the world (again, abstracting from the impact of potential changes in prices, regulation, and technology).

3.1.2. Oil Demand and Technical Progress

Whereas pure price-substitution implies reversibility, technological progress that is induced by price increases creates an irreversible and unidirectional effect that is not easily unwound, even when prices return to previous levels. Several distinct processes drive technical changes that influence oil demand. The first is exogenous change that is largely unrelated to specific changes in the price of oil or economic conditions. For example, airplane designs incorporated significant improvements in fuel efficiency, even prior to the price shocks of the 1970s. In an endogenous process, rising oil prices are the specific incentive that drives technical change. Automobile companies, for example, revamped their vehicle fleets after the 1970s to make passenger cars more fuel efficient; even when oil prices declined after 1985, those design innovations were never eliminated.

3.1.3. Alternative Vehicles and Competitive Fuels

Limited historical evidence exists by which to measure the strength and potential of inter-fuel substitution among competing fuels. In many countries, petroleum-based fuels appear to have no strong or viable competitor for powering transportation. That may be changing as countries have begun to make commitments to vehicles fueled by compressed natural gas, biofuels, and electrification. Additionally, companies may increasingly pursue gas-to-liquid processes as a technological option that substitutes relatively inexpensive natural gas for oil in the production of diesel fuels. Energy security and climate mitigation policies may accelerate these oil-reduction trends.

3.1.4. Demand Response to Oil Prices

If future oil supplies are expected to be scarcer than today, future oil prices will rise and curb some of the growth in demand; but, by how much? This question has probably attracted more of the attention of energy economists and commodity investors than any other issue during the last few decades. A major conclusion consistent with the findings of most studies is that the longer-run demand response to any gasoline price increases occurring over the next twenty years is likely to be several times larger than the short-term response that is initially apparent (Dahl and Sterner 1991 and Goodwin, Dargay et al. 2004). The response of consumption to price is the combined effect of many different decisions. Utilization decisions impact the gasoline market by reducing traffic activity and the number of miles driven by households. Over a longer period, household response to higher prices is also magnified as the vehicle fleet is retired and replaced.

The price elasticity of oil demand seems to be declining lately within the United States and perhaps more broadly within the OECD. Many countries outside of the OECD maintain large fuel subsidies that impose a wedge between crude and product prices (Arze del Granado et al. 2010). Removal of those subsidies, which have become quite expensive to maintain, would increase fuel prices to the end-user and thereby reduce future oil demand. The lack of data and estimates for the emerging countries limits our ability to foresee how these changes will influence oil markets in greater detail.

3.2. Oil Supply Availability and Costs

Despite significant gains achieved via enhanced oil recovery technologies, conventional oil supplies are diminishing in many fields located outside of the Middle East. Development of unconventional resources to offset this decline will be very important, but the cost, availability, and scale of resources such as Alberta's oil sands are as yet unknown. At the same time, oil supply prospects, even from conventional resources, may improve in certain areas. New oil may be discovered in relatively unexplored regions and reserve appreciation in known resource basins remains an important source of new additions. Technical progress will probably continue to reduce exploration and development costs significantly, as well as to enhance the safety and security of operations that extend further into frontier areas. Governments may reduce oil supply barriers by rolling back production royalties and taxes, and by easing constraints on leasing and acreage.

3.2.1. Resources and Geological Availability

Oil resources are scattered across the globe in formations with very different characteristics. Based upon its world oil assessment of 2000, the United States Geological Survey (2003) estimated that there were 1,898 billion barrels of remaining conventional oil and natural gas liquids, excluding cumulative volumes that had already been produced. These geological estimates are based upon likely discoveries, given the prevailing oil prices and available technologies present in 2000.

These conventional resources are supplemented by considerably larger volumes of unconventional resources—heavy oil, oil sands, and oil shale—that require specialized extraction technologies and significant processing before the oil can be sold. Aguilera et al. (2009) estimate that the combined volume of conventional and unconventional oil would last for 132 years if production increased by 2% per year.

3.2.2. Resource Costs

For economists evaluating market conditions, resource costs, rather than total reserves, determine whether scarcity prevails. Many geological estimates do not distinguish between resources that are inexpensive to extract and those that are much more costly to develop and produce. To fill this gap, a useful concept is the resource availability curve—a schedule that represents the total known resource base that could be developed at each successively higher-cost level.

Aguilera et al. (2009) derive an availability curve for conventional and unconventional petroleum resources. They estimate 7 TBOE (trillion barrels of oil equivalent) of conventional resources and 4 TBOE of heavy oil, 5 TBOE of oil sands, and 14 TBOE of oil shale with average production costs usually considerably higher than the comparable costs for conventional oil. The cost estimates for these unconventional petroleum resources are very uncertain and subject to change. To be useful, any long-run cost estimates should reflect production expanded to scale and the considerable learning that will accumulate through experience in developing these resources. Oil prices may well overshoot these long-run cost estimates during intervening years when additional unconventional sources are not yet large enough to meet growing demand.

3.2.3. Oil Supply from Competitive Regions

Producers outside the major exporting countries are generally considered as competitive price takers. Market prices must cover the marginal cost of producing the last unit of these supplies, including both the direct expenses and the firms' opportunity cost of drilling for oil, rather than engaging in another economic activity. If resource depletion is a factor, each supplier will also consider the opportunity cost of current extraction relative to future production. At higher prices, firms can justify exploring for and extracting more costly resources, and doing so earlier rather than later.

Two major trends are driving oil supply from regions outside of OPEC: the depletion of reserves that are easy to extract and the improvement of oil exploration and production technologies. The combined effects have led to an increase in mega-projects aimed at resources that were formerly inaccessible, either commercially or technically. Such projects include the Alberta oil sands, the deep water resources of the Gulf of Mexico, and the pre-salt deposits offshore of Brazil.

3.3. OPEC

The major oil exporters are sufficiently large to influence as well as to respond to price. They have market power. However, the extent to which market power has been exercised is less certain. The previous empirical literature leaves many questions regarding the impact of decisions and actions taken by OPEC. The data tends to support multiple competing theories, without definitively excluding any particular behavioral model. Analysts choose their favorite hybrid; they seldom test all versions. There is clearly room for additional research on the nature of OPEC and its evolution.

3.4. Long-term Models

The long-run behavior of the oil market has received considerable study through the application of computer models. Models can be classified by many different criteria, but we find it helpful to distinguish structural models from computational models. Both approaches take fundamental microeconomic theories about the objectives, constraints, and behaviors of market actors into consideration at their core. These theories are distilled into a mathematical structure, allowing for interaction between the actors within a specific market context. The primary distinction between the two categories is the level of complexity and detail; computational models have significantly more detailed representations of the market at the cost of model run time. They also have increased data requirements and may offer less straightforward interpretations.

Research into the formal modeling of the oil market began largely as a response to the oil crisis of 1973. The initial goal was to understand the role of OPEC decision making and its impact on the market price. Since that time, as the oil market has changed, and the research community has become more international, structural models have been applied in analyzing a wide range of issues involving oil. The major structural approaches include simulation, optimization, and game-theoretic frameworks.

In simulation models, the behavior of actors in the market is represented by a specific function contingent on market conditions. This function can be based either on some rule-of-thumb (such as a target price or target capacity utilization rule), or on historical econometric estimates of past behavior. Depending on the researcher's focus, the behavior of different agents may be described in various levels of detail. In general, OPEC is given more complex behavior, while non-OPEC producers follow a simple supply curve, often one that exhibits constant price elasticity. Of course, the researcher's goal is to develop rules or functions that are descriptive of actual behavior.

In an optimization model, at least one agent actively chooses its behavior to maximize an objective function, typically related to profit or welfare. For models of the oil market, the optimizing agent is generally assumed to be OPEC, or some subset of that organization. OPEC chooses a level of production to maximize the present value of profits, while taking how the resulting price will influence the decisions of competitive producers and consumers into account. While some models may have sophisticated representations of the limits to the knowledge available to the optimizing agent, in many cases, the optimizer is given complete foresight of the future path of the market. With the optimization approach, the researcher seeks to understand what a market player must do to obtain his best outcome.

In game-theoretic models, two or more agents are assumed to have market power, or at least some influence on each other's welfare. They attempt to take actions that are optimal, given their anticipation of what the other agent will do. Each agent is also assumed to take into account the strategic behavior of other actors in the market. A game-theoretic approach may be useful when it is necessary to explicitly consider the consequences of rivalry and competition between different large players in the market—for instance, when evaluating the incentives for individual OPEC members to deviate from established production quotas.

Computational models share many attributes with structural models and are largely distinguished by the sheer number of details included. The complexity of the models makes them costly to build and maintain and the level of detail makes it difficult to establish the impact of any one model choice. However, computational models facilitate certain types of analysis that are impossible with a structural model: detailed impacts upon individual stakeholders, specific technological scenarios, and full policy analysis. Moreover, one approach to computational modeling, so-called computable general equilibrium models, has been used extensively to investigate fuel substitution opportunities and the broader energy sector impacts of global greenhouse-gas emissions policies. Computational models also facilitate the division of labor in the modeling effort by dividing the project into distinct sub-modules.

Due to their cost and complexity, computational models are relatively scarce, but with cheaper computer power, they are becoming more common. Still, computational models are typically confined to institutions such as the International Energy Agency and the Energy Information Administration.

3.5. Research Gaps in Long-term Oil Markets

While there has been significant effort representing the long-term behavior of oil markets using models of all sorts, a great deal of work remains to be done. As new technologies are developed, demand grows, new kinds of resources are exploited, and relationships in the market change; the theories and models we apply to the oil market need constant re-evaluation. A few topics stand out as significant open questions in our understanding of the long-term behavior of the market going forward: demand behavior, modern OPEC behavior, producer welfare, and resource depletion.

3.5.1. Demand Behavior

With the exception of the large computational models, most oil models do not have a very sophisticated or detailed representation of the demand side of the market. Understanding demand dynamics would be useful not only in explaining recent price movements, but also in exploring the impacts this degree of demand variation has on oil-producing nations. Marked variation, but especially unpredictability, of demand presumably affects the welfare of producers, not just consumers, and may change the nature of their capacity investment decisions. Three major topics in demand behavior stand out as top candidates for further exploration: (1) the high rate of demand growth in developing countries, (2) the asymmetric response of oil demand to price changes, and (3) the role of technology in altering the energy intensity of oil-consuming activities.

3.5.2. Security and Climate Policy

Closely aligned with demand issues is the inclusion of other energy market dynamics that produce viable substitutes for oil-based products for transportation. Governments are adopting policies to accelerate the shift consumption away from oil through mandates, taxes, and subsidies—all in response to concerns about energy security and global climate change. To derive meaningful results, the broadening range of available substitutes for petroleum-based fuels requires the simultaneous evaluation of multiple fuel markets, rather than oil-only analysis.

3.5.3. Modern OPEC Behavior

In the late 1970s, OPEC was modeled by many to be a monopolist in the world oil market. One author once referred to it as a 'clumsy" cartel (Adelman 1980). Models developed in late 1970s and early 1980s examined a number of different theories regarding OPEC's behavior and market power. However, OPEC and its members have evolved through time and observations gleaned from the 1970s are now outdated.

In the most recent two decades, the global view of OPEC has changed. OPEC is no longer considered definitively as a cartel that exercises market power by regulating output. Smith (2009) suggests that OPEC has been restraining investment in new oil production capacity in recent years and thereby has contributed to higher prices in a market with very rapid demand growth. Although research efforts to study OPEC's behavior either econometrically or theoretically have diminished compared to prior years, there remains a need for new theoretical models describing OPEC; these models should be tested with detailed data culled from recent years.

3.5.4. Producer Welfare

Many of the market-power models treat OPEC production decisions as if they were made by a profit-maximizing firm or cartel. When trying to understand the impact of OPEC production decisions on global oil prices and consuming nations, such a formulation may be an adequate approximation of the decisions made by the organization. However, in reality, as sovereign nations, both political and economic concerns drive decision making. Oil-producing nations may constrain prices in order to maintain favorable relationships with other nations, or they may sell oil at a discount in their home market to benefit domestic consumers. It may make more sense to view the nations as maximizing welfare rather than maximizing profit.

Unfortunately, when moving from models that consider profit to ones that try to measure welfare, modeling techniques increase in complexity and require greater information on the national economy as a whole. While some models (De Santis 2003) have previously approached this important question, a great deal of work remains to be done in this area.

3.5.5. Resource Depletion

Oil reserves are finite and production will become more expensive and perhaps eventually hit a peak (Hubbert 1962). It remains unclear when such a peak will occur and whether it will be based on a lack of available resources or the lack of sustained crude oil demand. In fact, the threat of peak oil has loomed over the horizon since the dawn of the petroleum age, but consistent resource discoveries, unconventional resources, and technological breakthroughs have so far managed to expand oil supplies and may continue to mitigate crude resource scarcity for the foreseeable future. As discussed elsewhere (Smith 2012), it is not even clear that a peak in the production of oil, if it does occur, would be a harbinger of impending scarcity.

4. Short-Run Oil Price Drivers and Models

Generally speaking, conclusions regarding the short-run behavior of oil prices are even less certain than our knowledge of the factors that drive long-term trends. In large part, this is due to the relatively short history of investigation into short-run fluctuations, as well as recent changes in the composition and liquidity of short-term oil markets that have only begun to be sorted out.

Modeling short-run changes in the oil market requires different techniques, depending upon the specific issue under investigation. Financialization, in particular, has made the oil futures and other derivatives market more liquid and perhaps more influential, while the number of participants in financial markets has increased because of hedging and investment opportunities. The use of high-frequency data may be required to consider all the relevant details in short-term models, but much of that data is not available in the public domain. The primary goal of short-term models is to provide a better understanding of short-term price movements and to create short-term forecasts. In contrast with long-term models, short-term models do not usually seek to determine what the future equilibrium path for oil prices will look like. Instead, they attempt to forecast prices or price changes that are expected to be observed in the near future. This is typically attempted with the help of reduced-form models that estimate parameters of statistical models that best describe short-run price movements without considering the fundamental forces of supply and demand. Short-term models also use the powerful financial theories concerning arbitrage and risk-taking in an attempt to infer market expectations from observed future prices.

4.1. Critical Observations

During the previous decade, the oil market experienced significant short-term upsets, one the most important of which was the boom-bust price cycle during 2008. That particular episode challenged the ability of conventional models to provide adequate explanations and forecasts of oil prices. Many studies have looked to find structural explanations, but there still is no consensus on the underlying economic causes. In addition to the high levels of price, a higher level of volatility has been observed in the oil market in recent years. For the first time, a change of $100 per barrel in only four months was observed in oil prices from July to November 2008.

These trends are not limited to the oil market; financial activity and turmoil in commodity markets in general have increased. The volume of investment in commodity index funds, overall futures market trading activity (as revealed by the open interest in all contract maturities), and correlations among commodity prices, as well as between commodities and equities, have increased by varying degrees. Forward curves have become substantially flatter at times, indicating that futures prices at varying maturity dates are now moving more closely with each other and also with spot prices. Financialization may act as a double-edge sword; it increases market liquidity and facilitates price discovery and risk management. However, it also creates more opportunities for some traders who would attempt to distort and manipulate futures prices.

Against this backdrop, there appear two overriding challenges for the modeling community. First, is the need to examine whether futures trading causes artificial movements in the spot price of oil or not, and, if so, to trace out the expected remedial effect of alternative regulatory reforms. Second, is to assess if and how financial variables can be used to forecast future price paths more accurately than methods that are based on fundamental analysis alone.

4.2. Fundamental Drivers

Certain economic factors have played a fundamental role in recent price changes. Supply and demand shocks, together with the continuous flow of news and uncertainty that surrounds them, are the primary drivers underlying short-run oil price dynamics. The impact of these shocks is magnified by the low elasticities of both short-run oil supply and demand. Hamilton (2009) demonstrates that under specific assumptions about the elasticities of supply and demand, one can explain the 2008 boom-bust price cycle just by using fundamental supply and demand factors. A caveat is that the price predictions drawn from such models are extremely sensitive to the specific magnitude of the presumed elasticities. Nevertheless, short-term supply and demand drivers are believed to be able to describe most of the observed price changes. This section reviews these fundamental drivers.

4.2.1. Short-term Supply Drivers

During 2005-08, available inventories were depleted while major oil-producing countries held low levels of spare capacity. Considering the inverse relationship between spare capacity and spot oil prices, and the inelastic supply in the short-term, this has led to higher price levels.

Short-term supply shocks have also influenced the oil market. The Deepwater Horizon oil spill in the Gulf of Mexico and the revolution in Libya are two recent examples of such events. Consider first the deep water Horizon spill. The methods of obtaining liquid fuels are becoming increasingly reliant on advanced and capital intensive technologies. From deep water drilling, to the processing of oil sands, to advances in refining, the oil market is changing its risk profile. While engineers are constantly working to perfect control systems and reduce the chance of failures, the potential for damage from any single catastrophe is increasing. Furthermore, with the increasing lumpiness of production from the trend towards more complex megaprojects, the supply impact of a single outage (or addition) is increasing, potentially leading to greater price volatility (Skinner 2006).

4.2.2. Short-term Demand Drivers

The short-run demand for oil is also relatively price inelastic. There are four main reasons for this. First, oil consumption levels cannot change quickly, due to the existing stock of vehicles and other equipment that uses oil. Second, in the OECD countries, oil consumption is less responsive to price changes because the share of consumers' energy expenditures as a fraction of their total incomes is relatively low. Third, oil demand in developing countries is largely driven by steady income growth and industrialization. Fourth, the demand impacts of crude oil price changes are in many cases offset by government subsidies or taxes.

Macroeconomic news also influences oil prices. As incomes increase and economies expand, more energy will be used for transportation, heating, and cooling. Hicks and Kilian (2009) utilize a direct measure of global demand shocks based on revisions of professional forecasts of real GDP growth. They show that recent forecast surprises are associated primarily with unexpected growth in emerging economies. According to this line of research, markets have been repeatedly surprised by the strength of this growth.

Finally, U.S. foreign exchange and interest rates exert an influence on the price of oil. The price of oil (in USD) increased by more than 600% from January 2002 to July 2008. The same increase in terms of the Euro was less than 300% as the Euro gained strength during that interval. As this example suggests, depreciation of the U.S. currency may either lead or at least contribute to an increase in oil prices (which are typically expressed in U.S. dollars). Fluctuations in interest rates influence the value of oil in the future relative to its value today, which can lead to changes in production, consumption, and storage decisions. In addition, changes in interest rates prompt changes in the prices of financial derivatives accordingly.

4.2.3. News and Information Signals

In financial markets, the price is believed to reflect all publicly available information. Newly released information about future events will have a proportionate impact on today's price. All kinds of news are relevant: information regarding the economic growth of different countries, the prices of other commodities, currency rates, major countries' stock market movements, and many other factors. The flow of information can change prices frequently and sharply. However, to have any impact, the news must be credible.

Previous research shows that not all announcements made by major players in the oil market (OPEC, IEA, etc.) are credible. To better understand short-run price movements, it is important to distinguish between relevant, credible announcements and ones that are ignored by the market. An important step in conducting this analysis is to consider the incentives of the issuers of information: specifically, whether those objectives are aligned with the truthful revelation of information. A signaling framework and a forecast model can be used to simulate the effect of new announcements and analyze their incentives.

4.3. Price Forecasting Approaches
Most short-term oil market models focus exclusively on oil price and its statistical time series properties. In contrast, structural models explicitly specify and attempt to estimate the impact of changes in oil demand and/or supply. This distinction means that short-term price models are mainly limited to the task of forecasting, rather than providing economic interpretation of the sort required for policy analysis. Despite the rather large number of recent short-term price models that have appeared in the literature, significant opportunities remain for further study.

4.3.1. Reduced Form Models
Reduced form models take advantage of financial and structural data and employ econometric tools to build a model and estimate its parameters. These models are usually applied to forecast a specific variable (e.g., world oil price). They differ primarily in terms of the complexity of the statistical structure that is assumed to fit the data. Three contrasting specifications have been used to study oil price data: autoregressive moving average (ARMA), vector autoregression (VAR), and structural vector autoregression (SVAR). Each approach has its own advantages and, at the conceptual level, no one approach is superior to the others. Therefore, the choice among the models should be dictated by the observed statistical properties of the time series involved in the analysis.

If the reduced form models are applied for purposes beyond simple forecasting, however, serious problems arise. These problems center on the concept and interpretation of "causality," a term that plays an often misunderstood role in many short-run time-series analyses. Causality is, of course, central to the study of policy analysis. To be successful, policy makers must be able to anticipate the consequences of their actions. Will trading limits cause volatility to decrease? Will producing from the strategic petroleum reserve cause prices to decline? And so on. The cause and effect relationships that are implicit in these questions represent something stronger than the statistical tendency of two variables to move together, which is not evidence that an exogenous change in one variable will cause another resulting change in the other variable. Therefore, it is essential when contemplating short-term forecasting models to understand that a finding of "Granger–causality," which is based on patterns of correlation, neither proves nor disproves that a fundamental causal relationship links one variable to another. To the extent that a fundamental structure is added to the short-term approach in the form of a SVAR, it is also important to keep in mind that the structure that is assumed to link the variables in a causal chain is typically dictated by convenience, as when a diagonal pattern of variable exclusions is adopted in order to permit the model to be solved recursively; or, when a priori constraints are imposed on the size of key parameters to achieve identification of causal relations. Of course, if the constraints are untested and inappropriate, so may be the causal relations.

In summary, short-term statistical models will continue to flourish, based in part on the availability of additional high-frequency pricing data and in part due to increased scrutiny of financial investors in the oil market. It will be imperative for both the producers and consumers of this research to keep in mind the fundamental limitations of these time-series methods and to tailor their inquiries to questions that can properly be answered with the tools at hand.

4.3.2. Financial Models
Financial models are a more recent brand of oil price models that extend statistical analysis to some of the newer time series (futures prices and options) with guidance from relevant hypotheses developed in the theory of finance. Since options and futures contracts convey information about the future, they have been considered as a first step in incorporating financial data in oil models. However, futures prices may include a risk premium that varies through time, and therefore, they do not represent a simple expectation about the price that will prevail in the future. It has been shown, for example, that "no change" forecasts are more accurate than forecasts based on futures prices (Alquist, Kilian et al. 2010).

Pagano and Pisani (2009) document significant time-variation in the risk premium and use the degree of capacity utilization in U.S. manufacturing and oil inventory levels as proxies for this variation. They demonstrate how one can find expected future prices based on the combination of futures prices and the risk premium. Thus, if one could model and forecast the risk premium when combined with market data, it should be possible to obtain estimates of future expected prices. Given the potential value of this ability to producers and consumers alike, further research into determinants of the risk premium seems warranted.

4.3.3. Structural/Financial Hybrid Models

Hybrid models, combinations of structural and financial models, are motivated by the need to produce short-term forecasts that are more consistent with supply and demand frameworks. These models are calibrated to base-case forecasts of a long-term model, with outcomes that are adjusted based on the flow of new market information and short-term economic responses. Relevant new market information would include price observations from futures markets, forecasts in demand growth, and supply shocks (e.g., the reduction in Libya's production during 2011). Hybrid modeling requires estimates of both short-term and long-term elasticities with which to simulate price responses. The model takes information signals as input and generates price and quantity paths as output. In light of the Efficient Market Hypothesis, the market responds instantly to the new forthcoming information. Further efforts to incorporate theories of commodities and storage might lead to models capable of forecasting inventory changes and the movement of futures prices as well. (e.g., Routledge, Seppi, and Spatt 2000).

4.3.4. Modeling Volatility

Market price volatility can be estimated either from backward-looking historical data or from forward-looking financial derivatives using implied volatility (Szakmary et al. 2003). Indeed, even for models where volatility is not of direct concern, a researcher might need to know how volatility and price shocks lead to changes by consumers and producers. For example, the use and production of oil are heavily tied to existing capital stock and capacity investments. Price shocks, even over a relatively short time frame, can have lasting impacts on demand and supply for years to come through their impact on capital investment. Monte Carlo methods and artificial neural network technology could be applied to simulate supply and demand shocks and to estimate the benefits of major producers adopting strategies that stabilize prices, but that is all dependent on first developing an understanding of how the use of excess capacity and stockpiles influences volatility.

4.4. Analytical/Theoretical Models and Insights

Financial aspects of oil markets are not well explored. Studies are still trying to confirm a range of theoretical hypotheses about the operation of the financial markets and to identify the most important financial drivers. These include models that do not try to simulate or forecast the whole oil market. Instead, they use partial equilibrium or econometric techniques to try and understand short-term market movements more accurately and to distinguish among competing theoretical hypotheses.

During 2000-08, when oil prices were increasing, investments in commodities markets also increased significantly. This triggered the question of whether the price rise of 2008 represented a financial bubble of some kind or not. Brunnermeier (2009) defines a speculative bubble as characterized by the following elements: (1) prices are higher than the fundamental value, (2) a group of investors buys the asset based on the belief or sentiment that they can sell it to others later at a higher price, and (3) such beliefs or sentiments cannot be supported by fundamental factors.

Studies on the role of financialization can be categorized into two groups: conceptual models and statistical tests. The former type of analysis consists of deductive arguments for accepting or denying the hypothesis that an increase in financial activity will cause prices to rise more than what fundamental factors would dictate. The logical validity of these arguments rests solely on the underlying assumptions independent of any empirical evidence. The latter type of analysis focuses on quantitative relationships between trending variables to find statistical patterns of predictability.

A few studies cite conceptual arguments to advance the claim that excessive investment in commodity index funds might have played a role in creating the bubble. However, conceptual analysis alone cannot establish the strength or magnitude of the effect. Thus, additional empirical research is needed to clarify the picture. Certain conceptual relationships remaining so far are still rather inscrutable, even after they have been quantified. For example, Tang and Xiong (2010) find a link between increased price correlations among different commodities and the growing volume of commodity index investments. However, there is no indication, theoretical or otherwise, that higher correlations are good or bad.

In any event, elevated correlations are not evidence of a bubble. Regarding the possibility of a bubble induced by financialization, it is useful to remember that price movements in futures markets with rising index fund investment have not been moving uniformly upward (Irwin, Sanders et al. 2009). Moreover, Headey and Fan (2008) show that prices of many non-financial commodities—commodities that were not financialized—displayed similar dynamics as the financialized commodities, despite having no influx of speculative financial investors. There is considerable room for additional research into the price movements of all commodities, whether they are financialized or not. The parallel movements suggest the presence of some common factors beyond financialization and research is needed to identify and measure the influence of those factors. It seems likely that any progress in this direction will depend on a more complete appreciation of the role of common demand shocks, inventories, and convenience yields.

4.5. Statistical Tests

Researchers commonly perform statistical causality tests to describe the temporal relationship between speculators' trading activity, oil price movements, and volatility. As noted above, these tests using Granger causality establish causality not in a structural sense, but only confirm whether the observed movement in one variable precedes the changes observed in another variable. The difference is important: although one might move a picnic inside just before it starts raining, moving the picnic doesn't cause the rain. With that caveat in mind, and using non-public data, the Interagency Task Force on Commodity Markets (2008) studied the dynamic relation between daily price changes and changes in the positions of various categories of traders. They found that some trader positions can be predicted as a response to price changes, but not the reverse. Sanders and Irwin (2011) find evidence that larger long positions by index traders Granger-cause lower market volatility. This result is contrary to the popular belief that index traders' activities increase market volatility.

There is some additional evidence on the other side of the argument and the conflicting conclusions are an invitation to pursue further both conceptual and empirical research into the causes of commodity price movements. One example is the group of studies that evaluate whether or not statistical characteristics of oil price movements match the pattern of an explosive bubble. In contrast with explosive bubbles that prevailed for several months in the copper and nickel markets, Gilbert (2010) finds only weak evidence for an explosive bubble in the oil market, and that it appears to have endured for only a few days in July 2008. Even so, do we know what caused it, or why it subsided? Further, a few studies report some evidence, conceptual as well as empirical, that financial activities were driving the oil price away from its fundamental value during 2008. Although fundamental factors are important in his analysis, Einloth (2009) suggests that speculators may have been building inventories from March to July in 2008 based upon evidence that spot prices rose further after convenience yields had begun to fall. Singleton (2011) finds significant empirical support that investor flows influenced excess returns from holding oil future contracts of different maturities, after controlling for a number of other exogenous factors.

In summary, there have been many studies, but as yet no absolute consensus on the causes of the oil price boom and bust of 2008. Although there exists only limited statistical evidence that the price cycle represented a speculative bubble caused by an influx of financial traders, the matter remains the subject of great debate among researchers, policy makers, and the general public. The value of any further work that helps to clarify this issue would be substantial.

4.6. Prescriptive Models

Short-term modeling is a relatively new approach. Some studies have tried to build a theoretical framework for interactions between the financial markets and the physical markets. These prescriptive studies usually simplify the details of the actual market and examine various phenomena that would be expected to occur under certain conditions. The main goal of this deductive approach is to understand how the market works, rather than forecasting or simulating with high accuracy.

For example, Deaton and Laroque (1996) and Routledge, Seppi, and Spatt (2000) consider storage agents in the commodities' markets and determine how the levels of inventories should change with uncertainty and how forward curves should behave in such settings. Routledge, Seppi, and Spatt interpret the concept of convenience yield as an option that storage agents will exercise at an optimal time. Allaz (1992) develops a generic commodity market model (1992) to demonstrate that, depending on the relative strength of the hedging and strategic motives, a producer's optimal position in forward markets may be either short or long. Brandts, Pezanis-Christou, and Schram (2008) study of Cournot (quantity) competition and Liski and Montero's (2006) inquiry into a potential link between forward contracting and collusion are further examples. The stylized nature of modeling that lies behind all of these studies invites extensions that explore the robustness of the findings to more realistic depictions of the agents who trade in these markets.

5. The Role of Saudi Arabia in the Global Oil Market

The influence of Saudi Arabia on the global oil market is indisputable. Saudi Arabia's role and decision parameters since the discovery and production of oil in the Kingdom have been determined by different factors. Al-Moneef (2011) discussed this issue and highlighted four important factors.

The first factor is the size and production life of Saudi Arabia's oil reserves. For the past fifty years, Saudi Arabia has had very large crude oil reserves, equivalent to 20% of the world's proven reserves.

The second factor is the diversity of Saudi Arabia's export outlets. Saudi Arabia is exporting to the U.S., Europe, and the Far East. This diversity of outlets (and crude types exported) offers Saudi Arabia marketing flexibility and highlights the international consequences of its policies. In addition, Saudi Arabia is exporting its oil from two domestic terminals, the Arabian Gulf and the Red Sea, to the rest of the world.

The third aspect is the Kingdom's large crude oil production capacity. Saudi Arabia maintains a large excess capacity that is available to face supply disruptions and demand surges. Saudi Arabia's excess capacity in the past three decades since 1980 averaged 60% of OPEC's (and of the world's) excess production capacities, while its share in OPEC's and the world's production averaged 32% and 12% respectively during the period. This unused capacity averaged 35% of Saudi oil production during the 1982-1990 period, 13% during the 1990s, and 14% in this decade. OPEC's averages over these three periods were 17%, 6%, and 4%, respectively.

While the other OPEC members' excess capacities depend on market conditions, Saudi Arabia made an official policy since the mid-1990s, of maintaining 1.5-2 MBD excess oil production capacity at all times. Saudi Arabia's role has been very useful to soften the impact of major oil supply interruptions, such as the Iran-Iraq war, Iraq's invasion of Kuwait, the Venezuela crisis in 2003, Hurricane Katrina in 2005, and the Libyan crisis in 2011. These actions helped in lessening oil market volatility and stabilizing oil prices.

The fourth facet is the role of oil in Saudi Arabia's economy. For the past three decades, oil has represented 35% of Saudi Arabia's GDP, 84% of its government revenues, and 90% of its merchandise exports. These rates explain the high interdependence between the Kingdom's domestic and international oil policies.

These four factors have pushed Saudi Arabia to develop its own oil industry through its national oil company Saudi Aramco. The company was created through the purchase by Saudi Arabia of the assets of the four American companies operating in the Kingdom. Saudi Aramco was entrusted with the tasks of managing and developing the hydrocarbon resources of the Kingdom to achieve its development objectives, executing the government energy policies, and developing the technical skills needed in that sector.

Saudi Arabia's oil policies are geared towards efficiency and sustainability, which involves stable oil markets and an efficient oil industry that is able to play a strong role in the oil sector. In the face of environment uncertainties, Saudi Arabia is investing in research and development projects such as research centers, universities, and companies.

Regarding the role of Saudi Arabia in OPEC, it has been as important for OPEC as OPEC has been for Saudi Arabia (as suggested by R. Mabro, Oxford Institute for Energy Studies 2001). The roles of OPEC and Saudi Arabia have evolved in line with market changes. Such changes include the diversity of market players, the influence of the financial markets on the physical markets, the energy policies of consumer countries, and climate change, as well as energy security concerns.

Since the influence of the financial market on the physical oil market is increasing, Saudi Arabia has acknowledged the new market reality and adopted a policy of urging the international community to exert some regulatory oversight, as well as transparency measures, over the means of transactions in such markets. In order to stabilize the market, Saudi Arabia has been working with OPEC and IEA to reach better predictability. The Kingdom is also promoting the strengthening of the producer-consumer dialogue, among other things, by strengthening the role of the International Energy Forum (IEF), created in 2003 and entrusting it to coordinate the Joint Oil Data Initiative (JODI) to enhance the flow of timely and accurate oil data worldwide.

In the early 1990's, Saudi Arabia realized that the challenges of climate change would add to oil supply and demand uncertainties and so it integrated its climate-change policy with its oil policy. Saudi Arabia considers energy security as a two-dimensional concern: supply security (the availability, diversity, and reliability of energy supplies at all times) and demand security (the predictability, efficiency, and growth of energy demand in line with economic growth).

Saudi Arabia is expected to continue playing a dominant role on the global oil market. The Kingdom will continue its efforts to ensure sustainable oil supply to the world with stabilized long-term prices at reasonable levels. At the same time, it will go on with its investments in the oil and gas sectors to ensure adequate supplies and sustainable economic growth. It is expected to maintain an excess capacity of 1.5 to 2 MBD in order to face supply crises efficiently. Finally, Saudi Arabia's oil policy will be defined in dialogue with other producers and consumers, in order to address the environmental, investment, and price volatility challenges as a whole.

6. Conclusion

The complexity of the world oil market has increased dramatically in recent years and new approaches are needed to understand, model, and forecast oil prices today. In addition to the rapid financialization of the oil market, many fundamental structural changes have affected physical markets for oil. Financial instruments now communicate information about expected changes in the underlying fundamentals much more rapidly than in the past, so the implications of both financial and physical developments are clearly linked.

Casual evidence of the closer relation between financial and physical markets may be found everywhere. The prices of long- and short-dated contracts have started moving more closely together. Sudden supply and demand adjustments, including those related to China's economic growth, the Libyan uprising, and the Deepwater Horizon oil spill have changed expectations in ways that affect both current and futures prices. Although volatility appears to have increased, financialization has arguably made price discovery more robust and expectations more transparent. Most empirical economic studies suggest that expectations regarding fundamental drivers and their future trends shaped prices during the 2004-08 cycle, although over-exuberant expectations cannot be ruled out completely, based on available evidence.

With increased price volatility, major exporters are now considering ways to provide more price stability, which is needed to improve long-term production and consumption decisions. Managing excess capacity, primarily within OPEC, but also in the strategic stockpiles held by major consuming nations, has historically been an important factor in keeping world crude oil prices stable during periods of sharp demand and supply shifts. To what extent would the expansion of excess capacity alter market expectations in the current environment? Would the result be greater price stability in the face of uncertainties regarding, for example, the rate of Asian economic growth, the debt crisis in some European countries, the restoration of Libyan production, and heightened tensions between Iran and the west? OPEC can pursue price stabilization strategies more effectively if the causes and consequences of volatility are better understood and if OPEC members can coordinate on the use of additional oil production capacity.

Within the context of long-term oil price drivers, the role of Saudi Arabia in the energy market is quite important. Maintaining and expanding Saudi crude oil capacity, if undertaken, would provide a supply cushion to lessen oil price volatility. Unfortunately, one does not know the magnitude of these effects because there is uncertainty about the parameters influencing supply and demand behavior. History tells us that there have been periods when expansions in Saudi output stabilized oil prices, for example, in 1991 during the first Gulf War. It also reveals that there have been other periods when oil prices continued rising despite Saudi expansion, for example in 2008 leading up to the financial crisis.

In evaluating any decision regarding the use of excess capacity, it is important to know what other factors are moving oil prices at the same time. Another important aspect of Saudi Arabia's role in the oil market involves continued oil exploration efforts and the development of new fields that would allow production to keep pace with the growing global oil demand in the long run. Saudi Arabia's role also includes the maintenance of excess capacity that could be released immediately in periods when oil shortages suddenly emerge in the market.

Apart from the short-run consequences of price volatility, we must learn from the important structural changes that have occurred in oil markets after major price increases, because similar events are likely to happen again in the future. Partially motivated by government policies, the automobile industry dramatically improved vehicle fuel efficiency in the mid to late 1970s. Seismic imaging and horizontal drilling in the early 1980s expanded production capacity in countries outside OPEC. Recent improvements in shale gas technologies are now being extended to shale oil as well, resulting in expanded oil supplies in areas recently considered prohibitively expensive. The search for alternative transportation energy sources continues with expanded research into compressed natural gas, biofuels, diesel made from natural gas, and electric vehicles. Which of these factors, or others, will produce the next game-changing impact on the oil industry?

Many fundamental aspects of the world oil market remain unclear. After 40 years of research, there exists no credible, verifiable theory about the behavior and influence of OPEC. It is evident that OPEC members do not consistently act like a monolithic cartel. Empirical evidence suggests that at times members coordinate supply reductions and at other times they compete with each other. Output can be managed either by production in the short-term, or by limiting investment to expand capacity in the longer-term. Clearly, these are complementary strategies, but how can or should they be coordinated? Regional political considerations and broader economic goals beyond oil also must enter the calculations of each OPEC member country. These influences have also changed rapidly as the economies of OPEC members have been transformed dramatically during the past two decades; financial needs for exporting oil now weigh heavily in their decision-making and their actions continue to have a strong effect on the rest of the world.

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Ali Nouria

Impact of the Recent Regulatory Changes on the UCITS CTA Market

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1. UCITS CTA Market Overview

UCITS CTA funds have experienced exponential growth over the last four years. The number of funds has grown from 9 to 55 funds from January 2008 to September 2012. The assets under management have surged from EUR 1.57 billion to EUR 6.09 billion over the same period. Exhibit 1 illustrates the progression of both the number of funds and assets managed by CTA managers in UCITS format. The first UCITS CTA funds were launched mainly by managers based in Europe who were advising onshore vehicles. The market really began to pick-up after the summer of 2009, with large offshore CTA managers coming into play. Since then, the assets under management for UCITS CTA funds have more than doubled.

Exhibit 2 illustrates the portion of UCITS CTA funds that are using index structures versus fund structures in terms of the number of funds and the assets under management (as of September 2012). Although the funds using the index structure represent only one quarter of all funds, they account for about half of all assets under management in the strategy. Of the 10 largest UCITS CTA managers, 7 managers are using the index structure.

This dichotomy can be explained by the fact that the leading and oldest CTA managers favor the index structure. While recent regulatory changes may only concern a subset of CTA managers, they will affect the largest and best- known firms.

2. Index Based Approach versus Direct Approach

Since its introduction in 1985, the UCITS Directive has banned investments in physical commodities or in products linked to commodities, such as commodities derivatives. For this reason, the first UCITS CTA funds launched have no allocation to single commodity instruments.

However, CTA managers have explored other routes to implement their investment strategies, while maintaining exposure to commodities and complying with the UCITS Directive at the same time. One solution, which CTA managers developed was to make use of the index section of the Directive, rather than focusing on the fund section. UCITS indices are governed by different rules than funds and the current rules governing indices are generally simple and flexible enough to accommodate most CTA strategies. In order to be eligible, an index has to meet the following criteria:

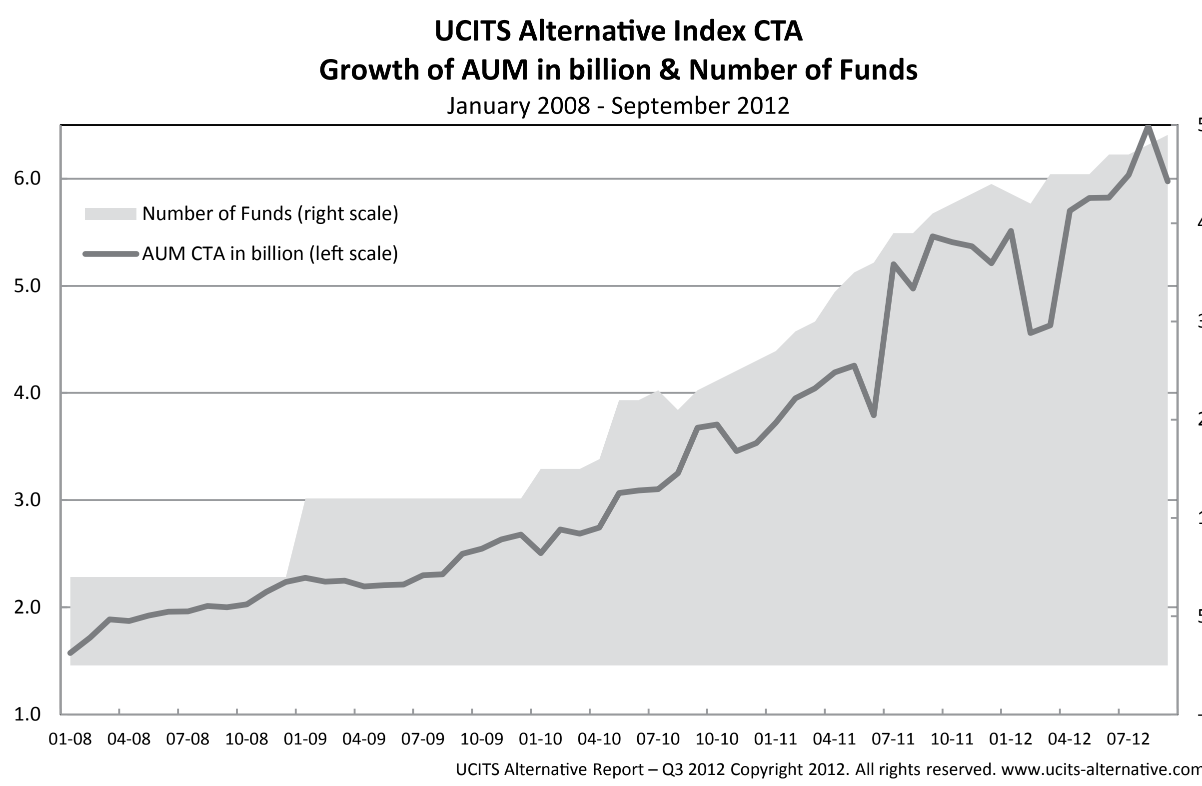
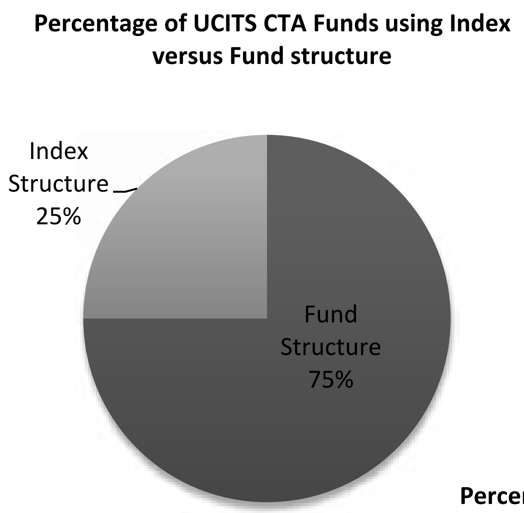


Exhibit 1 UCITS CTA Growth in AUM and Number of Funds
Source: Pirrong (2005)



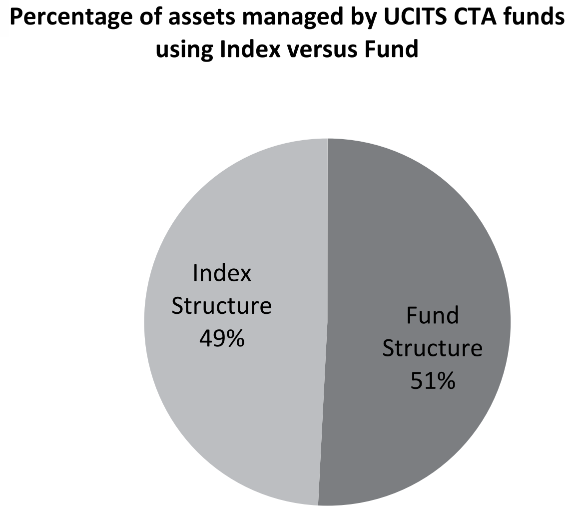


Exhibit 2 Breakdown of UCITS CTA funds using Index versus Fund structure
Source: Alix Capital / UCITS Alternative Index - www.ucits-alternative.com

- Provide sufficient diversification.
- Be representative of an adequate benchmark for the market to which it refers.
- Be published in an appropriate manner.
- Be independently managed from the management of the UCITS.

In practice, an index replicating the original strategy is created. The performance of this index is then replicated in the UCITS vehicle through a total return swap.

The use of this index structure offers several advantages. First, in terms of portfolio management, it allows an allocation into commodities instruments, as well as higher concentration limits. Second, it enables managers to handle only one pool of assets that can be then replicated in various investment formats, including offshore funds, UCITS, and managed accounts. Finally, it makes it possible to replicate the existing strategy without tracking error.

Nonetheless, using an index has a number of drawbacks. The performance replication comes at a cost and introduces an additional counterparty, the swap provider, which adds an extra layer of risk.

For many market participants, the rules governing UCITS indices were perceived to be too loose and were seen as a loophole in the regulation that could eventually damage the Directive's reputation. The UCITS index rules were designed to be as flexible as possible in order to accommodate most financial indices, but they were not developed as a way to circumvent the Directive's spirit by authorizing investment in otherwise non-eligible assets such as commodities. This dilemma motivated the European Securities and Markets Authority (ESMA) to review and strengthen the rules governing indices.

3. ESMA New Regulation Proposal-UCITS Eligible Indices

In the Report and Consultation Paper published on July 25th 2012, entitled Guidelines on ETFs and Other UCITS Issues: Consultation on Recallability of Repo and Reverse Repo Arrangements, ESMA introduces new guidelines governing the implementation on UCITS eligible indices. While the scope of the paper covers numerous issues, some of the guidelines directly impact UCITS CTAs that are using the index structure. ESMA's view is that an index shall be transparent and replicable if it is to qualify as UCITS-compliant and thereby benefit from the strong UCITS brand attached to the framework.

Specific sections of the paper have a direct impact on the use of this structure for CTA managers.

Rebalancing Frequency

ESMA declares that: "A UCITS should not invest in a financial index whose rebalancing frequency prevents investors from being able to replicate the financial index." Indices which are rebalanced on an intra-day or daily basis will not be acceptable in UCITS funds. This means that CTA managers who are rebalancing their portfolio more frequently than weekly will no longer be able to use this approach.

For some long-term trend following CTA managers weekly rebalancing may be acceptable, but many managers are employing shorter-term strategies that require more frequent rebalancing and they are directly impacted by the new regulation. The consultation paper specifies that technical adjustments may be made on an intraweekly basis and shall not be considered as rebalancing. Each regulator will have to determine what constitutes technical rebalancing.

Transparency

Calculation methodology

ESMA states UCITS should not invest in financial indices for which the full calculation methodology to, inter alia, enable investors to replicate the financial index is not disclosed by the index provider. The text further specifies that this includes providing detailed information on index constituents, index calculation, re-balancing methodologies, and index changes and indicates that this information should be easily accessible, free of charge, to investors and prospective investors.

This point is the most controversial one from a managerial perspective, as it concerns the development of intellectual property and competitive edge. CTA managers invest very substantial resources to develop and maintain their trading models. If the results are made directly available to everyone, they will think twice before choosing an implementation technique that obliges them to disclose those models.

Index constituents

ESMA states that: a UCITS should not invest in financial indices that do not publish their constituents together with their respective weightings. Again, the text specifies that the information should be easily accessible, free of charge, to investors and prospective investors. ESMA, however, adds that the weightings may be published after each rebalancing on a retrospective basis.

This is also a problematic issue for CTA managers and some managers have raised concerns over the possibility that competitors could re-engineer their models by analyzing the positions. For other managers, disclosing their positions would expose them to front running activities by other market participants and could have a severe impact on their returns.

4. Possible Outcomes

At this stage, a number of technical issues need to be clarified and each regulator may have a slightly different interpretation on how to implement the proposed changes. In any case, CTA managers will face a choice when these changes are implemented. Their options are described below.

4.1 Keep the Index Approach

Keeping the index approach means accepting the constraints described above. Managers will have to disclose both their methodologies and positions fully and they will also have to limit the rebalancing frequency to a weekly schedule. While this last point might turn out to be less restrictive in its application, the issue of transparency will prove quite difficult for CTA managers to navigate. One possible solution would be composed of two parts: (1) the regulators will accept a broad strategy description, rather than a comprehensive one, and (2) the managers will disclose the index methodology, but not too frequently, and the disclosure will occur with sufficient delay.

If that is the case, some managers could continue to use the index section of the Directive. However, it is difficult to know if and how many funds will continue to use this structure. All of the CTA managers we have discussed the proposals with (representing 50% of the CTA funds using the index approach) have stated that they could not accommodate the proposal as it is currently drafted.

4.2. Use the Fund Approach and Abandon Commodity Exposure

A number of CTA managers have built up competitive products and raised substantial assets without exposure to commodities by focusing on non-commodity futures. However, this is not applicable to all managers or across all investment approaches, as it depends on the relative contribution of commodities to the overall strategy. For managers with little exposure to commodities, this might be an acceptable solution; in fact, some managers are already working on models that exclude commodities and they will, therefore, adapt to the constraint. However, for most managers this option is not realistic, given the level of allocation already given to commodities, or taking their unique characteristics in terms of diversification and correlation into account. For those who proposed to abandon the commodity exposure, it could take some time to convince investors that they can effectively run their strategy without exposure to this asset class.

4.3. Use the Fund Approach and Maintain Commodity Exposure

Over the last two years, the development of new structured financial instruments such as certificates has allowed some CTA funds to gain exposure to commodities while using the fund section of the UCITS Directive. Certificates are debt instruments that fall within the categorization of transferable securities and are used to either replicate the performance of the commodities exposure only, or that replicate the performance of an entire portfolio. Certificates are bound to the same restrictions that govern other investments in a UCITS fund and they cannot represent more than 10% of the fund's allocation.

The composition of the certificate is not governed by the UCITS rules and it can invest in non-eligible assets, such as commodity derivatives. However, the regulator requires a certain level of diversification of the assets held. Certificates also have to meet specific constraints in terms of independent valuation and liquidity. They require approval by the regulator and this is done on a case by case basis.

The use of certificates is not an ideal solution, since as with any structured instruments, they introduce an additional layer of costs for the UCITS; they pose additional risks as well.

In our view, a large portion of UCITS CTA managers with commodities exposure will select this route in the future, despite its drawbacks. Using certificates allows managers to maintain the desired commodity exposures while not having to comply with the upcoming index constraints.

5. Conclusions

While it is difficult to draw any final conclusions concerning the ultimate interpretation of the ESMA guidelines, it is clear that the majority of CTA funds using the index structure will have to rethink the way they implement their strategies.

The use of certificates seems to be the most obvious option to gain commodity exposure. It will be interesting to see the ESMA's position if all CTA managers start to use this approach. Commodities are an important asset class, which helps investors achieve diversification. A number of market participants are lobbying for their inclusion among the list of UCITS eligible assets. For example, the Alternative Investment Management Association (AIMA) recently published a position paper about UCITS V that advocates the inclusion of commodities instruments in UCITS. Among other issues, AIMA believes that the current treatment of commodity derivatives appears to be outdated and in contradiction with the investor protection concerns and the interest of investors in general. These restrictions are having a contrary effect to the spirit of the law.

Solutions for CTA managers to retain commodity exposure in the UCITS framework exist, but it is not beneficial to force managers to use complex procedures to gain exposure to a highly regulated, liquid and commonly used asset class. Further thoughtful discussion of these issues and appropriate adjustments will be helpful to the industry and the investors alike.

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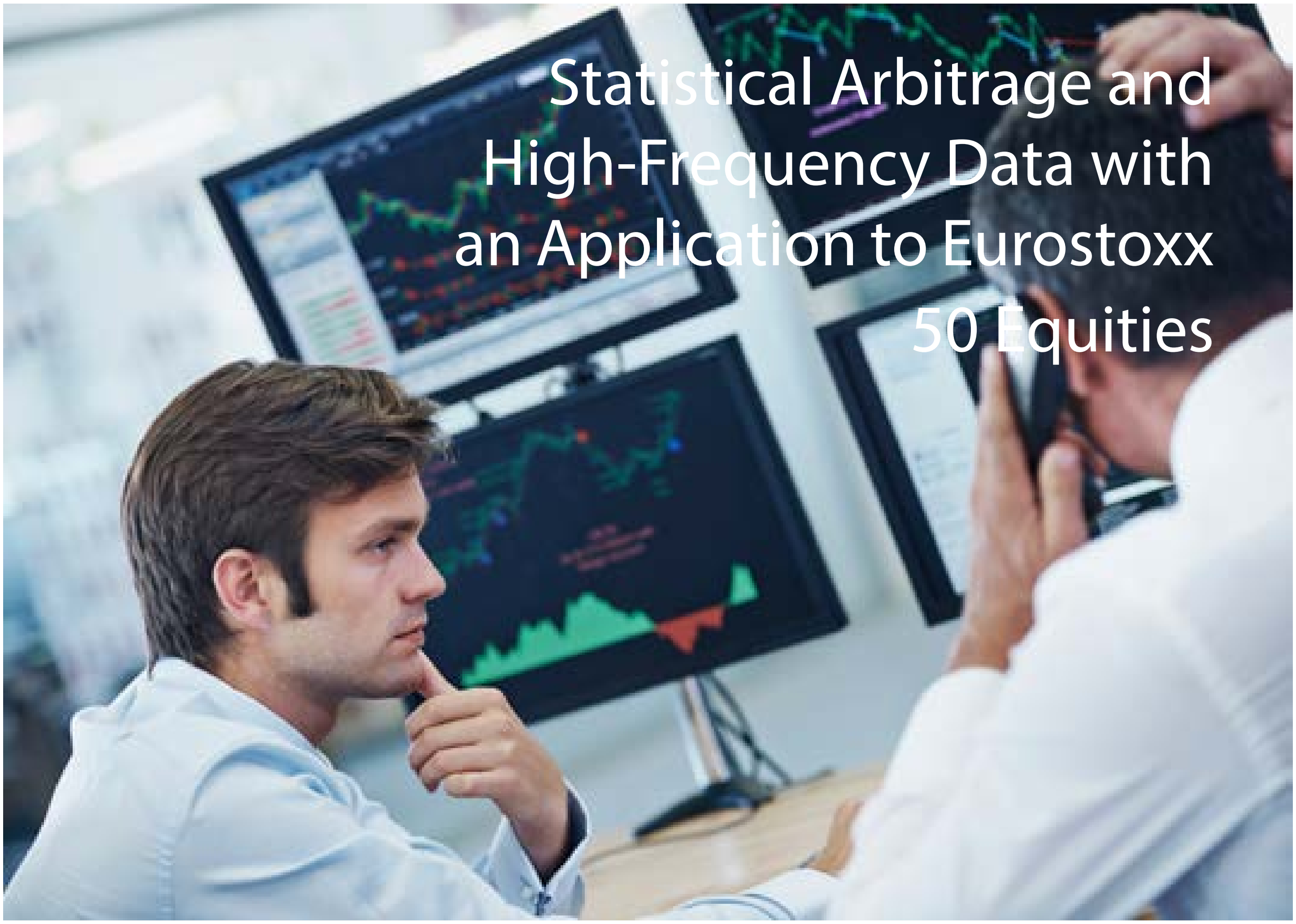

Statistical Arbitrage and High-Frequency Data with an Application to Eurostoxx 50 Equities

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1. Introduction

In this article, a basic pair trading (long-short) strategy is applied to the constituent shares of the Eurostoxx 50 index. A long-short strategy is applied to shares sampled at six different frequencies, namely 5-minute, 10-minute, 20-minute, 30-minute, 60-minute, and daily sampling intervals. The high frequency data spans from July 3, 2009 to November 17, 2009; our daily data spans from January 3, 2000 to November 17, 2009.

We introduce a novel approach, which helps to enhance the performance of the basic trading strategy. The approach consists of selecting the pairs for trading based on the best in-sample information ratios and the highest in-sample t-stat of the Augmented Dickey-Fuller (ADF) test, which is applied to the residuals of the co-integrating regression using daily data. We form the portfolios of five best trading pairs and compare the performance with appropriate benchmarks.

Another improvement we introduce is the use of the high-frequency data. The advantage of incorporating the high-frequency data is higher, potentially achievable information ratios[1] compared to the use of daily closing prices and thus higher profit potential for investors (Aldridge 2009).

Market neutral strategies are generally known for attractive investment properties, such as low exposures to equity markets and relatively low volatility (Capocci 2006), but recently the profitability of these strategies has deteriorated (Gatev et al. 2006). While Gatev et al. (2006) study goes only go back to 2002, the Hedge Fund Research Equity Market Neutral Index that started in 2003, does not show the supposed qualities for which market neutral strategies are known (i.e., steady growth and low volatility). The industry practice for market neutral hedge funds is to use a daily sampling frequency and standard co-integration techniques to find matching pairs (Gatev et al. 2006). This approach is useful because it best approximates the description of how traders themselves choose pairs. Thus, by modifying an already well-known strategy using intraday data, we may obtain an edge over other traders and we can compare the results of simulated trading using intraday data on various sampling frequencies with daily data.

2. Literature Review

The following section provides a brief review of the relevant literature.

2.1. Market neutral strategies

Pair trading, a well-known technique, was developed in 1980 by a team of scientists led by Wall Street quant Nunzio Tartaglia (Gatev et al. 2006). The strategy is widely documented in the existing literature, including Enders and Granger (1998), Vidyamurthy (2004), Dunis and Ho (2005), Lin et al. (2006), and Khandani and Lo (2007).

The general description of the technique is a pair of shares is formed where the investor is long one share and short the other share. The rationale is that there is a long-term equilibrium (spread) between the share prices and the shares will fluctuate around that equilibrium level (the spread has a constant mean). The investor evaluates the current position of the spread based on its historical fluctuations and when the current spread deviates from its historical mean by a pre-determined significant amount (measured in standard deviations), a spread position is established. The investor bets on the reversion of the current spread to its historical mean by shorting/going long an appropriate amount of each share in the pair. The appropriate amount of each share is expressed by the variable beta, which tells the investor the number of the shares of X he has to short/go long for each one share of Y. There are various ways of calculating beta: it can be fixed, or it can be time-varying. To make beta time-varying, we will use rolling ordinary least squares (OLS) regression, double exponential smoothing-based (DESP) model, and the Kalman filter.

2.2. Market Neutral Strategies and High Frequency Data

From an extensive review of literature there appears to be only one relevant study regarding high frequency market neutral trading systems (Nath 2003), which looks at market neutral strategies in the U.S. fixed-income market.

2.3. Co-integration

Co-integration is a quantitative technique introduced in a seminal paper by Engle and Granger (1987) that is based on finding long-term relationships between asset prices. Given its utility, co-integration might help identify potentially related pairs of assets. However, we will consider all of the possible pairs from the same industry, not only the co-integrated ones. We do this so that we will be able to measure whether the co-integrated pairs in the in-sample period perform better in the out-of-sample period than the non-co-integrated ones.

Another approach was developed by Johansen (1988), which can be applied to more than two assets at the same time. The result is a set of co-integrating vectors that can be found in the system. The spread between the assets is not the one with the lowest variance, as with OLS, but rather the most stable one in the long-term (Alexander 2001). According to Alexander, the Engle and Granger (1987) methodology is preferred in financial applications due to its simplicity and lower variance, which are important points to consider from a risk management perspective. Since we only deal with pairs of shares in this paper, we also prefer the simpler Engle and Granger (1987) methodology.

There are many applications of co-integration in the world of investing, for example, index replication, which exploits long-term qualities of co-integration and requires only occasional portfolio rebalancing (e.g., Dunis and Ho (2005) and Alexander and Dimitriu 2002). There are also market-neutral arbitrage strategies based on co-integration, where one enters a trade when a relationship deviates from the long-term mean and exits the trade when the spread has returned to the long-term mean. While Burgess (2003), Lin et al. (2006), and Galenko et al. (2007) refer to their strategies as high-frequency trading, they use daily closing prices among four world indexes, rather than intraday continuous or intraday minute data.

2.4. Time Adaptive Models

Dunis and Shannon (2005) use time adaptive betas with the Kalman filter methodology (Hamilton (1994) or Harvey 1981). The Kalman filter is a popular technique when time varying parameters need to be estimated (Choudhry and Wu 2009, Gomez 2005, Brooks et al. 1998, and Burgess 1999). These papers support the Kalman filter method as a superior technique for adaptive parameters. The Kalman filter is a forward looking methodology, as it tries to predict the future position of the parameters as opposed to using a rolling OLS regression (Bentz 2003).

Alternatively, DESP models can be used for adaptive parameter estimation. According to LaViola (2003a, 2003b) DESP models offer comparable prediction performance to the Kalman filter, with the advantage that they run 135 times faster.

2.5. Hedge Funds

The pair trading technique is used primarily by hedge funds and with regard to the type of investment strategy it falls under, there is a distinct hedge fund classification bearing the name equity market neutral funds (Khandani and Lo 2007 and Capocci 2006). Hedge funds employ dynamic trading strategies that are dramatically different from the ones employed by mutual funds and this enables them to offer investors more attractive investment opportunities (Fung and Hsieh 1997 and Liang 1999).

3. The Eurostoxx 50 Index and Related Financial Data

We use 50 stocks that formed the Eurostoxx 50 index as of November 17, 2009 (Appendix F). The data downloaded from Bloomberg includes six frequencies: 5-minute, 10-minute, 20-minute, 30-minute, 60-minute data (high-frequency data), and daily prices. We refer to all the data related in the minute dataset as high-frequency for brevity's sake.

Our database of minute data spans from July 3, 2009 to November 17, 2009.[2] Intraday stock prices are not adjusted automatically by Bloomberg for dividend payments and stock splits, so we adjust them accordingly.[3] Our database only includes the prices at which the shares were traded; although we do not consider bid and ask prices, some of our recorded trades were transacted at the bid and some at the ask. We have as many as 8,000 data points when data are sampled at 5-minute intervals for a 5-month period. For lower frequencies, the amount of data falls linearly with decreasing frequency. For example, in the case of 10-minute data, we have around 4,000 data points and for the 20-minute data, we have 2,000 data points.

The database that includes daily closing prices spans from January 3, 2000 to November 17, 2009. The data is adjusted for dividend payments and stock splits.[4] Some shares do not date back as far as January 3, 2000, and as a consequence, the pairs that they formed contain a lower amount of data points.[5]

In Exhibit 1, we provide the start and the end of the in- and out-of-sample periods for all of the frequencies. For high-frequency data, the in- and out-of-sample periods are the same length. For daily data, the in-sample period is much longer than the out-of-sample period. The start of the out-of-sample period is not aligned between daily and high-frequency data.[6]

We used the Bloomberg sector classification with the industry sector ticker. We divide the shares in our

	In-sample		No. points	Out-of-sample		No. points
5-minute data	03 July 2009	09 September 2009	4032	10 September 2009	17 November 2009	4032
10-minute data	03 July 2009	09 September 2009	2016	10 September 2009	17 November 2009	2016
20-minute data	03 July 2009	09 September 2009	1008	10 September 2009	17 November 2009	1008
30-minute data	03 July 2009	09 September 2009	672	10 September 2009	17 November 2009	672
60-minute data	03 July 2009	09 September 2009	336	10 September 2009	17 November 2009	336
Daily data	03 January 2000	31 December 2008	2348	01 January 2009	17 November 2009	229

Exhibit 1 Specification of the in- and out-of-sample periods and number of data points contained in each

database into 10 industrial sectors: (1) basic materials, (2) communications, (3) consumer cyclical, (4) consumer non-cyclical, (5) diversified, (6) energy, (7) financial, (8) industrial, (9) technology, and (10) utilities. Note that there is only one share in each of the diversified and technology categories (Appendix E) that prevents both these shares from forming pairs.

For our pair trading methodology, we select all the possible pairs from the same industry. This is not a problem with daily data, as we have daily closing prices for the same days for all of the shares in the sample. In contrast, at times with high-frequency data and for a given pair, one share has a price related to a particular minute while no price is recorded for the other share, due to no transaction having taken place in that minute. In such an event, unmatched prices were dropped out so that we were left with two price time series with the same number of data points in each, where the corresponding prices were taken at approximately the same moment (same minute). This situation presents itself only rarely, as these 50 shares are the most liquid European shares listed.

4. Methodology

In this section, we describe in detail the techniques that we use in simulated trading. First, we describe the Engle and Granger (1987) co-integration approach, then, we describe the techniques we used in order to make the beta parameter adaptive: rolling OLS, the DESP model, and the Kalman filter.

Since the Kalman filter proves to be a superior technique for the beta calculation (as shown later), only the Kalman filter is used for the calculation of the spread to obtain the final results that are presented in this paper.

4.1. Co-integration model

First, we form the corresponding pairs of shares from the same industry. Once these are formed, we evaluate whether the pairs are co-integrated in the in-sample period. We investigate whether the fact that some pairs are co-integrated helps to improve the profitability of the pairs selected. Thus, in the first stage we consider pairs that are co-integrated and pairs that are not co-integrated.

The 2-step approach proposed by Engle and Granger (1987) is used for the estimation of the long-run equilibrium relationship, where the first step in the OLS regression shown below is performed.

$$Y_t = \beta X_t + \varepsilon_t \tag{1}$$

In the second step, the residuals of the OLS regression are tested for stationarity using the ADF at 95% confidence level (Said and Dickey 1984).

4.2. Rolling OLS

To calculate the spread, first we need to calculate the rolling beta using rolling OLS. Beta at time t is calculated from n previous points.

$$Y_t = \beta_t X_t + \varepsilon_t \tag{2}$$

However, the rolling OLS approach is the least favoured in the literature due to the ghost effect, lagging effect, and drop-out effect (Bentz 2003).

We optimized the length of the OLS rolling window using genetic optimization.[7] For more details on genetic optimization see Goldberg (1989) and Conn et al. (1991). The objective of the genetic optimization was to maximize the average in-sample information ratio for 6 randomly[8] chosen pairs[9] at a 20-minute sampling frequency. The optimized parameter was the length of the rolling window for the OLS regression in the in-sample period. Thus, the genetic algorithm was searching for the optimum length of the rolling window in the in-sample period with the objective of maximizing the in-sample information ratio. The best values found for the in-sample period were subsequently used in the out-of-sample period as well. The same 6 pairs at the same sampling frequency with the same objectives were also optimized in case of the DESP model and the Kalman filter.

The average OLS rolling window length for the 6 pairs found using the genetic algorithm was 200 data points; this window was then used for all of the remaining pairs and frequencies in the out-of-sample period.

4.3. Double Exponential-smoothing Prediction Model

DESP models are defined by two series of simple exponential smoothing equations.

First, we calculate the original β_t series, where $\beta_t = \frac{Y_t}{X_t}$ at each time step. Once we have the β_t series, we smooth it using the DESP model. The DESP model is defined by the following 2 equations:

$$S_t = \alpha\beta_t + (1-\alpha)S_{t-1} \quad (3)$$

$$T_t = \alpha S_t + (1-\alpha)T_{t-1} \quad (4)$$

where β_t is an original series at time t, S_t is a single exponentially smoothed series, T_t is a double exponentially smoothed series, and α is the smoothing parameter. At each point t in time, the prediction of the value of β_t in time period t+1 is given by:

$$\tilde{\beta}_{t+1} = a_t + kb_t \quad (5)$$

$$a_t = 2S_t - T_t \quad (6)$$

$$b_t = \frac{\alpha}{1-\alpha}(S_t - T_t) \quad (7)$$

where $\tilde{\beta}_{t+1}$ is the prediction of the value of β_t in time period t+1; α is the level estimated at time t; b_t is the trend estimated at time t; and k is the number of look-ahead periods.

We optimized the α and k parameters present in Equations 3, 4, 7 and 5; the optimized values for α and k are 0.8126 and 30, respectively.

4.4 Time-varying Parameter Models with Kalman Filter

The Kalman filter allows parameters to vary over time and it is more optimal than a rolling OLS for adaptive parameter estimation (Dunis and Shannon 2005). Further details of the model and estimation procedure can be found in Harvey (1981) and Hamilton (1994).

The time-varying beta model can be expressed by the following system of state-space equations:

$$Y_t = \beta_t X_t + \varepsilon_t \quad (8)$$

$$\beta_t = \beta_{t-1} + \eta_t \quad (9)$$

where Y_t is the dependent variable at time t; β_t is time-varying coefficient; X_t is the independent variable at time t; and ε_t and η_t are independent uncorrelated error terms. Equation 8 is known as a measurement equation and Equation 9 as the state equation, which defines beta as a simple random walk in our case. We use a similar model to Dunis and Shannon (2005) and Burgess (1999). For the full specification of the Kalman filter model, see Appendix A.

We optimized the noise ratio (Appendix A). The resulting value for the noise ratio of 3.0e-7 was then used for all of the remaining pairs and frequencies.

5. The Pair Trading Model

The procedures described in this section were applied to both daily and high-frequency data. The pairs had to belong to the same industry to be considered for trading. In order to keep the strategy simple, this was the only restriction placed on our strategy. This leaves us with pairs that are immune to industry-wide shocks.

5.1. Pair Trading: a Self-financing Strategy

A pair trading strategy requires one to be long one share and short the other share. Pair trading is a so-called self-financing strategy (e.g., Alexander and Dimitriu 2002), meaning that an investor can borrow the amount of cash that he wants to invest, say from a bank. Then, to be able to short a share, he deposits the borrowed amount of cash with the financial institution as collateral and obtains borrowed shares. Thus, the only cost he has to pay is the difference between the borrowing interest rates paid by the investor and the lending interest rates paid by the financial institution to the investor. Subsequently, to go short a given share, the investor sells the borrowed share and obtains cash in return. From the cash he finances his long position. On the whole, the only cost is the difference between both interest rates (paid versus received). We consider a more realistic scenario in which an investor does not have to borrow capital from a bank in the beginning (e.g., the case of a hedge fund that uses capital from investors). This allows us to drop the difference in interest rates. Therefore, a short position would be wholly financed by an investor. In our first scenario, the investor would be paid interest from a financial institution which lends him shares; this interest was neglected for the ease of calculation. As our strategy proves robust and profitable, it does not affect our conclusions since it biases our results downward.

5.2. Spread calculation

First, we calculate the spread between the shares. The spread is calculated as:

$$z_t = P_{Y_t} - \beta_t P_{X_t} \quad (10)$$

where z_t is the value of the spread at time t; P_{X_t} is the price of share X at time t; P_{Y_t} is the price of share B at time t; and β_t is the adaptive coefficient beta at time t.

Beta was calculated at each time step using the three methods described in the methodological section, namely the rolling OLS, the DESP model, and the Kalman filter. We did not include a constant in any of the models; therefore, we obtain a model with fewer parameters to be estimated.

5.3. Entry and exit points

First, we estimate the spread of the series using Equation 10. The spread is then normalized by subtracting its mean and dividing by its standard deviation. The mean and the standard deviation are calculated from the in-sample period and are then used to normalize the spread for both the in- and out-of-sample periods.

We sell (buy) the spread when it is 2 standard deviations above (below) its mean value and the position is liquidated when the spread is within 0.5 standard deviations of its mean. We decided to wait for 1 period before we enter into the position to be conservative and ensure that the strategy is viable in practice. For instance, in the case of 5-minute data, after the condition for entry has been fulfilled, we wait for 5-minutes before we enter the position.

We chose the investment to be money-neutral, thus the amounts of euros to be invested on the long and short side of the trade will be the same.[10] As the spread is away from its long-term mean, we bet on the spread reverting to its long-term mean, but we do not know whether we will gain more from our long or short position.[11] We do not assume rebalancing once we enter

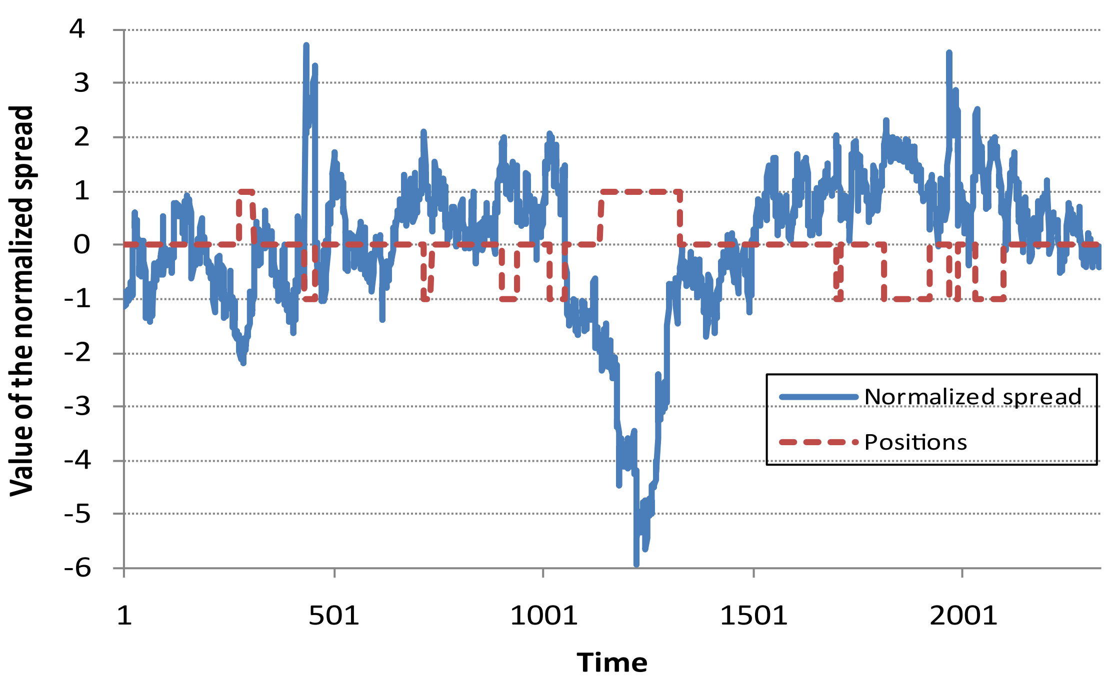

Exhibit 2 The normalized spread of the pair consisting of Bayer AG and Arcelor Mittal sampled a 20-minute interval

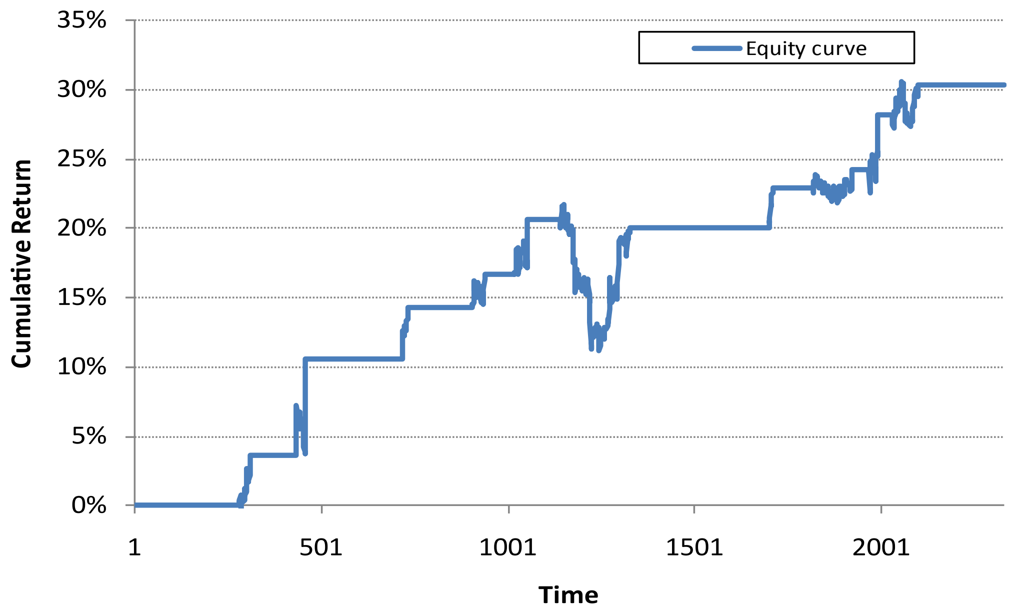

Exhibit 3 Cumulative equity curve in percent of the pair trading strategy applied to Bayer AG and Arcelor Mittal sampled at a 20-minute interval

into the position. Therefore, after an initial entry into the position, with equal amounts of euros on both sides of the trade, we do not rebalance the position, even when the positions cease being money-neutral due to price movements. Only two types of transactions are allowed by our methodology: entry into a new position and total liquidation of the position.

For an illustration, in Exhibit 2 we show the normalized spread and the times when the positions are open. When the dotted line is equal to 1(-1), the investor is long (short) the spread.

In Exhibit 3, we show the cumulative equity curve for the pair consisting of Bayer AG and Arcelor Mittal.[12] Note how the investment lost almost 10% around the mid-point of the sample period, as the position was entered into too soon and continued to move against the investor. Finally it reverted and recovered almost all of the capital lost.

In the next section, we explain the different indicators calculated in the in-sample period, in search of a link with the out-of-sample information ratio. As a result of our analysis, we offer a methodology for evaluating the suitability of a given pair for arbitrage trading.

5.4. Indicators inferred from the spread

All the indicators are calculated in the in-sample period. The objective is to find the indicators with high predictive power of the profitability of the pair in the out-of-sample period. These indicators include the t-stat from the ADF test (on the residuals of the OLS regression of the two shares), the information ratio, and the half-life of mean reversion.

5.4.1. Half-life of mean reversion

The half-life of mean reversion in number of periods can be calculated as:

$$Halflife = -\frac{\ln(2)}{k} \tag{11}$$

where is the median unbiased estimate of the strength of mean reversion from Equation 12 (Wu et al. 2000 and Dias and Rocha 1999). Intuitively, it is half of the average time the pair usually takes to revert back to its mean. Thus, traders should prefer pairs with a low half-life to those with a high half-life.

Equation 12 is called the OU equation and can be used to calculate the speed and strength of mean reversion (Mudchanatongsuk et al. 2008). The following formula is estimated on the in-sample spread:

$$dz_t = k\left(\mu - z_t\right)dt + \sigma dW_t \tag{12}$$

where μ is the long-term mean of the spread; z_t is the value of the spread at particular point in time; k is the strength of mean reversion; σ is the standard deviation; and W_t is the Wiener process. The higher the, the faster the spread tends to revert to its long-term mean. Equation 12 is used indirectly in the paper, since it is just the supplementary equation from which we calculate the half-life of mean reversion of the pairs.

5.4.2. Information ratio

We decided to use the information ratio (IR), a widely applied measure among practitioners, as it gives an idea of the quality of the strategy.[13] An annualized information ratio of 2 means that the strategy is profitable almost every month. Strategies with an information ratio around 3 are profitable almost every day (Chan 2009). For our purpose, we calculated the information ratio as:

$$Annualized\ Information\ Ratio = \frac{R}{\sigma}.\sqrt{hours\ traded\ per\ day.252} \quad (13)$$

where R is the average return we obtain from the strategy and σ is the standard deviation of return of the strategy. However, it is not a perfect measure and Equation 13 overestimates the true information ratio, if returns are autocorrelated (e.g., Sharpe 1994 or Alexander 2008).

6. Out-Of-Sample Performance And Trading Costs

6.1. Return calculation and trading costs

The return in each period is calculated as:

$$Ret_t = \ln(P_{X_t} / P_{X_{t-1}}) - \ln(P_{Y_t} / P_{Y_{t-1}}) \quad (14)$$

where P_{X_t} is the price of the share we are long in period t; P_{Y_t} is the price of the share we are long in period t-1; is the price of the share we are short in period t; and $P_{Y_{t-1}}$ is the price of the share we are short in period t-1.

We consider conservative total transaction costs of 0.3% one-way in total for both shares, similar to Alexander and Dimitriu (2002), for example. We are dealing with the 50 most liquid European shares in this paper. Transaction costs consist of 0.1%[14] of brokerage fee for each share (thus 0.2% for both shares), plus a bid-ask spread for each share (long and short),which we assume to be 0.05% (0.1% for both shares).

We calculate a median bid-ask spread for the whole time period for 6 randomly chosen stocks sampled at a 5-minute interval. We chose 6 stocks using the same randomization procedure that we used to select 6 random pairs for the genetic optimization purposes for rolling OLS, DESP, and the Kalman filter. The median value of the 6 median values of the bid-ask spreads was 0.05%. The bid-ask spread at any moment was calculated as:

$$Bid\ /\ Ask\ Spread = \frac{abs(P_A - P_B)}{avg(P_A + P_B)} \quad (15)$$

where P_A is the ask price of a share at any particular moment and P_B is the bid price at the same moment.

We buy shares that depreciates significantly, while we sell shares that appreciate significantly. Therefore, in real trading, it may be possible not to pay the bid-ask spread. The share that we buy is in a downtrend. The downtrend occurs because transactions are executed every time at lower prices. The lower prices are the result of falling ask prices, which get closer to (or match) bid prices, so effectively one does not have to pay bid-ask spread and will transact at or close to the bid quote. The opposite is true when prices of shares are rising.

AVERAGE VALUES	Fixed Beta	rolling OLS	DESP	Kalman
5-minute data	0.96	0.92	1.27	1.21
10-minute data	0.96	0.88	0.77	1.27
20-minute data	0.90	1.03	0.75	1.19
30-minute data	0.97	1.09	0.88	1.34
60-minute data	0.94	0.91	0.99	1.23
Daily data	0.49	-0.33	0.52	0.74

Exhibit 4 Out-of-sample information ratios for the simulated pair trading strategy at different frequencies. Transaction costs have not been considered

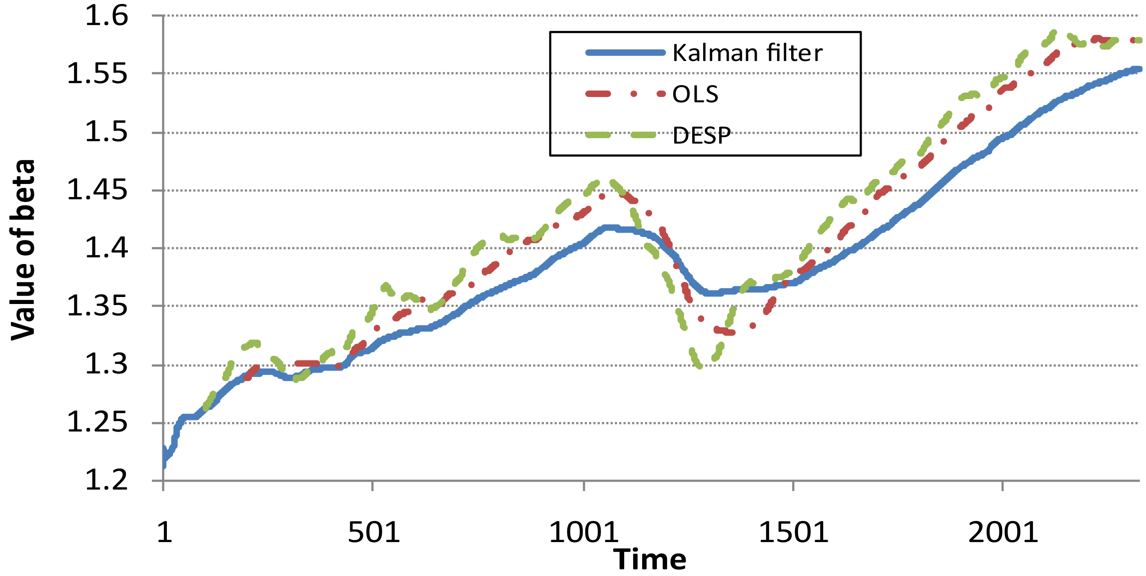

Exhibit 5 Various betas calculated for the Bayer AG and Arcelor Mittal pair sampled at a 20-minute interval

6.2. Preliminary out-of-sample results
In Exhibit 4, we present the out-of-sample information ratios, excluding transaction costs for the pair trading strategy at all of the frequencies. Results across all the three methods that we have used are displayed.

Results are superior for the Kalman filter method for most sampling frequencies. For this reason, we focus exclusively on this methodology in our further analysis. It is interesting to note that rolling OLS and DESP do not offer clearly better results than is the case where beta is fixed.

From Exhibit 4 it is also clear that higher sampling frequencies offer more attractive investment characteristics than daily data for all of the methodologies.

In Exhibit 5, we present adaptive betas that have been calculated using the three approaches mentioned previously. Both the OLS and DESP betas seem to fluctuate around the Kalman filter beta.

In Exhibit 6, we show the distribution of the information ratios, including transaction costs for the 20-minute sampling frequency with the Kalman filter that was used for the beta calculation.

From the above figure, it is clear that an average pair trading strategy is profitable and that pairs are mainly situated to the right of 0.

We also present the distribution of information ratios for daily data in order to investigate the difference between higher and lower sampling frequencies more closely (Exhibit 7).

Again, as shown in Exhibit 6, the majority of the information ratios are positive. Distributions of information ratios for other sampling frequencies can be seen in Appendices B-E.

The summary statistics for all trading frequencies are provided in Exhibit 8. The main difference between the daily data and high-frequency data is the maximum drawdown and maximum drawdown duration (Magdon-Ismail 2004). Both these measures are of primary importance to investors. The maximum drawdown defines the total percentage loss experienced by the strategy before it starts "winning" again. In other words, it is the maximum negative distance between the local maximum and subsequent local minimum measured on an equity curve and it provides a good measure of the downside risk for the investor (Appendix G).

The maximum drawdown duration is expressed as the number of days from the start of the drawdown until the equity curve returns to the same percentage gain as before. Both of these measures are important from a psychological standpoint, because investors might start questioning the strategy when it is experiencing a drawdown.

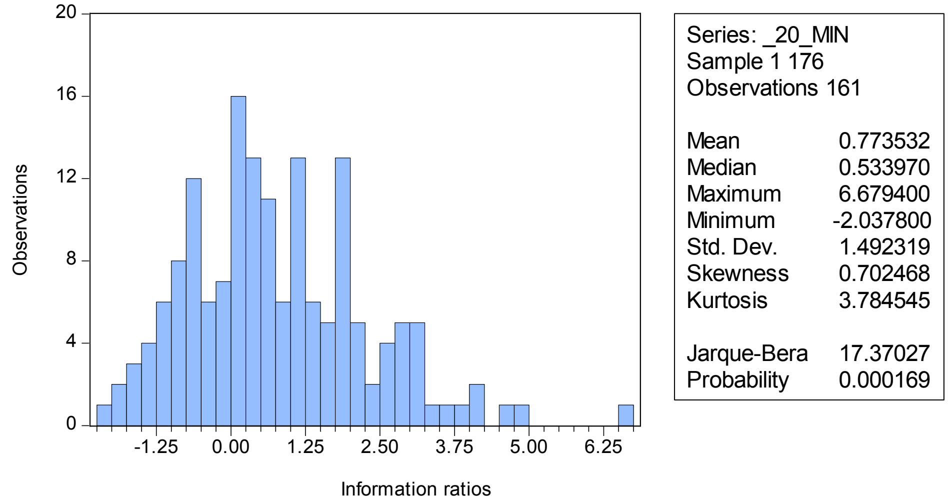

Exhibit 6 Distribution of information ratios for a 20-minute sampling frequency. One-way transaction costs of 0.4% have been considered

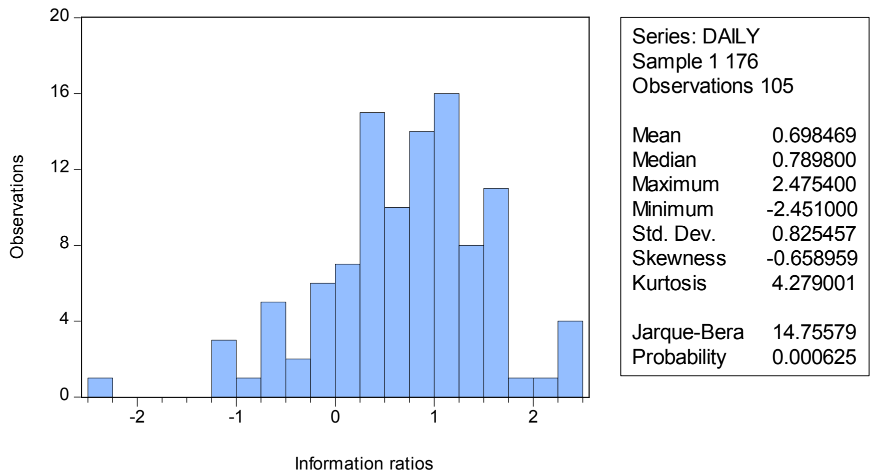

Exhibit 7 Information ratios of the pairs using daily sampling frequency. One-way transaction costs of 0.4% have been considered

Both statistics are significantly higher for daily data than for any higher frequency. The maximum drawdown for daily data is 13.61%, whereas it is 4.11% for high-frequency data. The maximum drawdown duration ranges from 5 to 20 days for the high-frequency data and is as much as 79 days for the daily data.

Information ratios (excluding trading costs) are slightly higher for high-frequency data, as was previously shown in Exhibit 4. When trading costs are considered, high-frequency data is more affected than daily data, due to the higher number of transactions. For instance, the information ratio for the 5-minute data drops from an attractive 1.21 to mere 0.26 when the trading costs are considered. The average information ratio of the pairs sampled at high-frequencies is 0.72, very similar to the daily sampling frequency (0.70). However, we consider very conservative trading costs, which excessively penalizes high-frequency data, so the information ratio achievable in real trading might be considerably higher.

6.3. Further investigations

We further analyze our results below and address several interesting issues from an investment perspective.

6.3.1. Relationship between the in-sample t-stats and the out-of-sample information ratios

We examine whether the in-sample co-integration of a given trading pair implies better out-of-sample performance. One can logically assume that a higher order of stationarity of the residual from the co-integration equation implies a higher level of confidence

AVERAGE VALUES	5-minute	10-minute	20-minute	30-minute	60-minute	Average HF	Daily
Information ratio (ex TC)	1.21	1.27	1.19	1.34	1.23	1.25	0.74
Information ratio (incl. TC)	0.26	0.64	0.77	0.97	0.97	0.72	0.70
Return (ex TC)	16.03%	17.58%	17.12%	20.25%	18.71%	17.94%	19.55%
Return (incl. TC)	1.92%	7.83%	10.33%	14.08%	14.08%	9.65%	18.62%
Volatility (ex TC)	17.55%	18.51%	18.57%	19.35%	19.57%	18.71%	29.57%
Positions taken	49	34	24	21	17	29	3
Maximum drawdown (ex TC)	4.09%	4.25%	4.07%	4.07%	4.08%	4.11%	13.61%
Maximum drawdown duration (ex TC)	5	10	10	20	19	13	79

Exhibit 8 The out-of-sample annualized trading statistics for pair trading strategy with the Kalman filter used for the beta calculation

in-sample t-stats vs. oos information ratio	5-minute	10-minute	20-minute	30-minute	60-minute	Daily
LOWER	0.04	-0.05	-0.18	-0.22	-0.26	-0.18
UPPER	0.32	0.23	0.13	0.10	0.09	0.22

Exhibit 9 95% confidence intervals of the correlation coefficients between t-stats generated in the in-sample period and the out-of-sample information ratios

that the pair will revert to its mean. Thus, we would expect a significant positive correlation between the t-stat of the ADF test on the OLS residuals and the out-of-sample information ratio. We perform this analysis on daily data only. We deal with intraday data later.
We bootstrap (with replacement) the pairs consisting of information ratios and t-stats.[15] The t-stat is obtained from the coefficient of the ADF test of the co-integrating equation. After bootstrapping (with replacement) the correlation coefficient 5,000 times at a 95% confidence interval, we obtain a lower/upper limits for the coefficients shown in Exhibit 9.

The in-sample t-stat seems to have certain predictive power for the out-of-sample information ratio, although not for all of the frequencies. The only frequencies for which the t-stat works are data sampled at 5- and 10-minute intervals. For all the other frequencies, the center of the distribution is either very close to 0 (20-minute and daily data), or slightly negative (30-minute and 60-minute data). For instance, 95% confidence intervals for daily data are almost perfectly centered around 0 (-0.18 and 0.22), implying that the true correlation coefficient might be 0.

6.3.2. Relationship between t-stats for different high-frequencies and pairs

In this paper, we have various sampling frequencies defined as high frequency. Those are data sampled at 5-, 10-, 20-, 30- and 60-minute intervals. In this section, we investigate whether there is a certain structure in their t-stats that could help us to reduce the dimensionality of higher frequencies. This would enable us to pick only one higher frequency representative of all the intervals for further analysis.

To do that, we apply principal component analysis (PCA) to all the high-frequency pairs (Jollife 1986). PCA is a statistical technique that tries to find linear combinations of the original assets accounting for the highest possible variance of the total variance of the data set. If there is a strong common behavior of the assets, (in our case, this would be the t-stats across different pairs and frequencies), just a few first principal components should suffice to explain the behavior of the entire data set.

As the first step to obtain the data suitable as an input to PCA, we form the matrix of t-stats from the ADF test. Each row of the matrix contains t-stats for different pairs (we have 176 rows, the same amount as the number of pairs) and each column contains t-stats for these pairs sampled at different frequencies (thus we have 5 columns, one for 5-, 10-, 20-, 30- and 60-minute interval). The matrix is normalized across the columns by subtracting the mean and dividing by the standard deviation of each column. In this way, we obtain a matrix with mean 0 and unit variance in each column.

The covariance of such a normalized matrix serves as an input for a PCA. The first principal component explains over 97.9% of the variation in the data, confirming that there is a clear structure in the dataset. This means that trading pairs have similar t-stats across all the frequencies. In other words, the columns of the original matrix are similar.

This finding is further reinforced by comparing variances between t-stats. From the original matrix of t-stats, we calculate variances for each frequency. We obtain 5 variances between the pairs (1 for each high frequency), which all vary around 0.58, quite a high variance for t-stats when considering that t-stats range from 0.18 to 2.83. Then we compute the variance of the t-stats for each of the 176 pairs across the 5 frequencies. These are much smaller in magnitude; the maximum variance is only around 0.14. The fact that the variances between different frequencies are small when considering each of the 176 pairs, but the variances between the pairs are high further demonstrates that t-stats tend to be similar across all of the frequencies for any given pair.

As a conclusion, we summarize that once a pair has been found to be co-integrated (in any time interval higher than the daily data), it tends to be co-integrated across all the frequencies. Hence, we only need to look at one frequency.

6.3.3. Does co-integration in daily data imply higher frequency co-integration?

We just demonstrated that there is a clear structure in the high-frequency dataset of the t-stats. The conclusion was that it is sufficient to consider only one higher frequency (here we decide for 5-minute data) as a representative for all of the high-frequencies. In this section, we investigate the relationship between the t-stats for daily data (computed from January 1, 2009 to September 9, 2009 for daily data) and the t-stats for 5-minute data (computed from the out-of-sample period for 5-minute data, i.e., September 10, 2009 to November 17, 2009).

We perform bootstrapping with replacement to obtain confidence intervals of the true correlation coefficient. The dataset is bootstrapped 5,000 times and the 95% confidence interval is -0.03/0.33.

The boundaries of the confidence interval imply that there is a possible relationship between the variables. The true correlation coefficient is probably somewhere around 0.15 (in the center of the confidence interval mentioned above). Thus, co-integration found in daily data implies that the spread should be stationary for trading purposes in the high-frequency domain.

6.3.4. Information Ratio: In-Sample and Out of Sample

Do the in-sample information ratio and the half-life of the mean reversion indicate what the out-of-sample information ratio will be? We showed above that there is a relationship between the profitability of the strategy and the stationarity of the spread computed from the t-stat of the ADF test. Here we try to find additional in-sample indicators (by looking at the in-sample information ratio and the half-life of mean reversion) of the out-of-sample profitability (measured by the information ratio) of the pair.

We follow the same bootstrapping procedure that we previously described in order to estimate the confidence intervals; the bootstrapping is performed 5,000 times,with replacement, as in other cases.

In Exhibit 10, we show the bootstrapped correlation coefficients between the in- and out-of-sample information ratios (not taking into account transaction costs) across all frequencies.

The confidence bounds indicate that the in-sample information ratio can predict the out-of-sample information ratio to a certain extent. Whereas in Exhibit 9 the t-stat only worked for 5- and 10-minute data, the information ratio works for data sampled 5-, 10-, 20-minute and daily intervals. On the other hand, the in-sample information ratio does not work well for 30- and 60-minute data. We assume that the relationship should be positive, whereas for 30- and 60-minute data, the center between the confidence bounds is negative and close to 0, respectively. Overall, the average lower/upper interval across all the frequencies presented is -0.06/0.26.

in-sample vs. oos information ratio	5-minute	10-minute	20-minute	30-minute	60-minute	Daily
LOWER	-0.02	0.10	-0.09	-0.26	-0.16	0.07
UPPER	0.31	0.42	0.26	0.07	0.15	0.32

Exhibit 10 95% confidence intervals of the correlation coefficients between information ratios generated in the in- and out-of-sample periods

half-life vs. oos information ratio	5-minute	10-minute	20-minute	30-minute	60-minute	Daily
LOWER	-0.18	-0.25	-0.24	-0.19	-0.15	-0.19
UPPER	0.08	-0.01	0.00	0.08	0.13	0.08

Exhibit 11 95% confidence intervals of the correlation coefficients between the in-sample half-life of mean reversion and the out-of-sample information ratios

AVERAGE VALUES	5-minute	10-minute	20-minute	30-minute	60-minute	Average HF	Daily
Information ratio IN-SAMPLE (incl. TC)	5.65	6.21	6.57	6.81	6.77	6.40	0.90
Information ratio (ex TC)	3.22	9.31	3.44	3.92	1.27	4.23	1.39
Information ratio (incl. TC)	2.27	7.71	2.58	2.88	0.75	3.24	1.32
Return (incl. TC)	21.14%	33.63%	15.16%	13.63%	5.27%	17.77%	18.50%
Volatility (ex TC)	9.30%	4.36%	5.88%	4.73%	7.02%	6.26%	14.03%
Maximum drawdown (ex TC)	3.02%	0.78%	1.19%	1.49%	1.42%	1.58%	4.26%
Maximum drawdown duration (ex TC)	7	17	18	33	34	22	55

Exhibit 12 The out-of-sample information ratios for 5 selected pairs based on the best in-sample information ratios

Next, we perform a bootstrapping of the pairs consisting of the in-sample half-life of mean reversion and the out-of-sample information ratio. We show the 95% confidence interval bounds of the true correlation coefficient in Exhibit 11. As we would expect, the lower the half-life is, the higher the information ratio of the pair. The extent of the dependence is slightly lower than the one presented in Exhibit 10. The average lower/upper interval across all the frequencies presented is -0.20/0.06. So we find that there is a negative relationship between the half-life of mean reversion and subsequent out-of-sample information ratio.

Thus, the two indicators presented here seem to have certain predictive power as to the out-of-sample information ratio of the trading pair.

7. A Diversified Pair Trading Strategy

Standalone results of trading the pairs individually are quite attractive, as shown in Exhibit 8, but here we try to improve them using the findings from the previous section. We use the indicators mentioned above to select the five best pairs for trading and present the results.

First, we present the results of using each indicator individually. The results of selecting five pairs based on the best in-sample information ratios are shown in Exhibit 12.

Information ratios improve for pairs sampled at the high-frequency and daily intervals. The improvement is the most noticeable for pairs sampled at the high-frequency intervals, when the average information ratio net of trading costs for the high-frequency data improves from 0.72 as in Exhibit 8 to 3.24. The information ratio for daily data improves as well (from 0.7 to 1.32). Most of the information ratios for the pairs sampled at the high-frequency intervals are above 2.

The maximum drawdown and maximum drawdown duration favour the pairs that are sampled at the high-frequency intervals as well. The average maximum drawdown for the pairs sampled at the high-frequency intervals is 1.58%, much less than the drawdown for the pairs sampled at a daily interval (4.26%). The maximum drawdown duration is 22 days on average for the high-frequency data, and 55 days for the daily data.

In Exhibit 13, we show trading results based on using the half-life of mean reversion as an indicator. Thus, five pairs with the lowest half-life of mean reversion were selected to form the portfolio.

The information ratios net of trading costs are not attractive, with 0.50 being the highest and -3.32 being the lowest. The average information ratio for the pairs sampled at the high-frequency interval is -0.75, which means that the average pair is not profitable. The information ratio of the pairs sampled at a daily interval is 0.5, which is profitable, but worse than the basic case shown in Exhibit 8. Thus, we decide not to consider the half-life of mean reversion as a prospective indicator of the future profitability of the pair.

AVERAGE VALUES	5-minute	10-minute	20-minute	30-minute	60-minute	Average HF	Daily
Information ratio IN-SAMPLE (incl. TC)	0.58	1.33	4.35	4.42	5.51	3.24	0.46
Information ratio (ex TC)	1.59	6.42	4.35	1.34	0.59	2.86	0.57
Information ratio (incl. TC)	-3.32	0.34	0.10	-0.85	-0.04	-0.75	0.50
Return (incl. TC)	-18.27%	1.25%	0.26%	-2.40%	-0.26%	-3.88%	6.71%
Volatility (ex TC)	5.50%	3.63%	2.63%	2.83%	7.01%	4.32%	13.43%
Maximum drawdown (ex TC)	0.81%	0.92%	0.93%	1.36%	1.84%	1.17%	3.07%
Maximum drawdown duration (ex TC)	3	7	16	29	34	18	57

Exhibit 13 The out-of-sample trading statistics for 5 pairs selected based on the best in-sample half-life of mean reversion

AVERAGE VALUES	5-minute	10-minute	20-minute	30-minute	60-minute	Average HF	Daily
Information ratio IN-SAMPLE (incl. TC)	2.16	2.37	3.32	3.39	3.71	2.99	0.38
Information ratio (ex TC)	12.05	6.13	1.47	-0.22	1.28	4.14	-0.05
Information ratio (incl. TC)	5.60	2.47	-1.18	-0.90	0.15	1.23	-0.08
Return (incl. TC)	13.53%	6.49%	-3.38%	-6.49%	0.69%	2.17%	-1.50%
Volatility (ex TC)	2.42%	2.62%	2.88%	7.23%	4.56%	3.94%	18.82%
Maximum drawdown (ex TC)	0.52%	0.57%	1.21%	1.19%	1.23%	0.94%	3.64%
Maximum drawdown duration (ex TC)	3	7	18	35	39	20	74

Exhibit 14 The out-of-sample trading statistics for 5 pairs selected based on the best in-sample t-stats of the ADF test

AVERAGE VALUES	5-minute	10-minute	20-minute	30-minute	60-minute	Average HF
Information ratio IN-SAMPLE (incl. TC)	1.08	1.25	0.75	1.18	1.34	1.12
Information ratio (ex TC)	6.86	8.95	4.62	3.73	2.40	5.31
Information ratio (incl. TC)	2.12	5.40	3.12	2.64	1.75	3.01
Return (incl. TC)	7.65%	18.96%	15.89%	16.28%	12.55%	14.27%
Volatility (ex TC)	3.61%	3.51%	5.09%	6.16%	7.15%	5.11%
Maximum drawdown (ex TC)	0.79%	0.66%	0.92%	1.03%	1.43%	0.97%
Maximum drawdown duration (ex TC)	4	5	5	10	13	7

Exhibit 15 The out-of-sample trading statistics for 5 pairs selected, based on the best in-sample t-stats of the ADF test for daily data

In Exhibit 14, we show the results of using the in-sample t-stats of the ADF test of the co-integrating regression as the indicator of the out-of-sample information ratios.

Focusing on the information ratios after transaction costs, they are worse than when the in-sample information ratio was used as an indicator. The out-of-sample information ratio after transaction costs is higher using the t-stats than using the in-sample information ratio only for a 5-minute data. For all the other frequencies, the in-sample information ratio is a better indicator.

In Exhibit 15, we present the results of using the t-stat of the ADF test for daily data (from January 1, 2009 to September 9, 2009) as an indicator of the out-of-sample information ratio of the pairs sampled at the high-frequency intervals. The average information ratio for all of the high-frequency trading pairs is around 3, which makes it the second best indicator after the in-sample information ratio.

We also include an equally-weighted combination of the indicators. We use the formula below:

$$Combined\_ranking = \frac{R_1 + R_2}{2} \qquad (16)$$

where R_1 and R_2 are the rankings based on the in-sample information ratio and the in-sample t-stat of the series sampled at a daily interval. In other words, we assign a ranking from 1 to 176 to each pair of shares based on the 2 indicators mentioned above. Then, we calculate the average ranking for each trading pair and reorder them based on the new ranking values. Finally, we form the portfolio of the first five trading pairs.

The trading results of the combined ratio are presented in the Exhibit 16.

AVERAGE VALUES	5-minute	10-minute	20-minute	30-minute	60-minute	Average HF	Daily
Information ratio IN-SAMPLE (incl. TC)	1.12	-0.81	-0.25	-0.04	0.99	0.20	0.20
Information ratio (ex TC)	0.73	3.43	4.11	6.61	8.01	4.58	0.43
Information ratio (incl. TC)	-0.52	1.75	2.92	5.25	6.78	3.24	0.35
Return (incl. TC)	-6.03%	9.42%	18.01%	26.92%	35.11%	16.69%	5.00%
Volatility (ex TC)	11.67%	5.40%	6.17%	5.13%	5.18%	6.71%	14.15%
Maximum drawdown (ex TC)	3.58%	1.11%	1.00%	1.05%	1.53%	1.65%	5.21%
Maximum drawdown duration (ex TC)	1,783	855	257	157	54	21	169

Exhibit 16 The out-of-sample trading statistics for 5 best pairs selected, based on combined ratio calculated according to Equation 16

AVERAGE VALUES	5-minute	10-minute	20-minute	30-minute	60-minute	Average HF	Daily
Information ratio IN-SAMPLE (incl. TC)	0.96	2.21	1.25	4.87	4.08	2.67	0.51
Information ratio (ex TC)	3.02	15.80	-0.05	2.03	-0.12	4.14	0.46
Information ratio (incl. TC)	1.30	7.60	-0.58	0.92	-0.52	1.74	0.43
Return (incl. TC)	7.61%	7.92%	-3.91%	4.33%	-4.49%	2.29%	6.81%
Volatility (ex TC)	5.87%	1.04%	6.78%	4.68%	8.63%	5.40%	15.96%
Maximum drawdown (ex TC)	0.71%	0.92%	1.81%	1.74%	1.85%	1.41%	5.65%
Maximum drawdown duration (ex TC)	4	8	19	38	61	26	40

Exhibit 17 Out-of-Sample Results

AVERAGE VALUES	Market neutral index	Eurostoxx 50	Daily Strategy
Information Ratio (incl. TC)	-1.04	0.54	1.32
Return (incl. TC)	-4.56%	15.34%	18.50%
Volatility (incl. TC)	4.36%	28.62%	14.03%
Maximum drawdown (ex TC)	6.20%	33.34%	4.26%
Maximum drawdown duration (ex TC)	188	44	55

Exhibit 18 In-Sample Annualized Trading Statistics

The average information ratio for the pairs sampled at the high-frequency intervals is 3.24. Unfortunately, the pair trading strategy using daily data only achieves an information ratio of 0.35 after transaction costs, which is worse than the original, unoptimized case.

We also combine the t-stat of the ADF test for a given high-frequency and information ratio and obtain attractive results. Although the average information ratio net of trading costs for the trading pairs sampled at the high-frequency intervals is higher than was the case in Exhibit 8 (when no indicator was used), the information ratios for the 20- and 60-minute sampling frequencies are negative, and thus results are not consistent across all of the high-frequency intervals. This, in our opinion, disqualifies the usage of this indicator for predicting the future profitability of the pairs.

Futher note that Exhibit 16 displays the out-of-sample trading statistics for 5 best pairs selected, based on the combined ratio of the in-sample t-stat of the ADF test and the in-sample information ratio

To summarize, we were able to improve the information ratios net of trading costs for daily data from around 0.7 as in Exhibit 8, to 1.3 as in Exhibit 12, using the in-sample information ratio as an indicator of the future profitability of the pairs.

Furthermore, we found that three different indicators heavily improved the attractiveness of the results for the pairs sampled at the high-frequency intervals. We were able to increase the out-of-sample information ratio from 0.72 as in Exhibit 8 (the average out-of-sample information ratio for all the 176 pairs sampled at the high-frequency intervals) to around 3, using the in-sample information ratio and the t-stat of the ADF test of the series sampled at a daily interval, and a combination of the two (Exhibit 12, 15, and 16).

Below, we compare the results of the pair trading strategy at both frequencies (an average of all of the high-frequency intervals and a daily one) with the appropriate benchmarks. In practice, one would choose only one high-frequency interval to trade, but here we look at an average, which represents all of the frequencies for reasons of presentation. In fact, pairs sampled at all

AVERAGE VALUES	Market neutral index	Eurostoxx 50	HF Strategy
Information Ratio (incl. TC)	0.90	0.78	3.24
Return (incl. TC)	3.55%	16.40%	17.77%
Volatility (incl. TC)	3.96%	21.10%	6.26%
Maximum drawdown (ex TC)	1.64%	8.31%	1.58%
Maximum drawdown duration (ex TC)	19	11	22

Exhibit 19 Out-of-Sample Annualized Trading Statistics

the high-frequency intervals are attractive for trading purposes when the in-sample information ratio is used as the indicator of the future profitability. Due to homogeneity, we also use the in-sample information ratio as the indicator for the pairs sampled at daily interval.

In Exhibit 17, we present a comparison of our pair trading strategy sampled at a daily interval with the results of a buy and hold strategy of the the Eurostoxx 50 index and the HFR Equity Market Neutral Index. The results span January 1, 2009 to November 17, 2009, with the out-of-sample period for our pairs sampled at a daily interval.

The Exhibit displays the annualized trading statistics compared in the out-of-sample period for the pair trading strategy sampled at daily interval, with the in-sample information ratio used as the indicator of the future profitability of the strategy

The strategy outperforms its primary benchmark, the HFR Equity Market Neutral Index, both on an absolute and risk-adjusted basis. While the Equity Market Neutral Index lost money during the period, our strategy was profitable without showing excessive volatility relative to its return. It also outperformed the corresponding market index, the Eurostoxx 50 index.

In Exhibit 19, we compare the results of the average high-frequency pair trading strategy with the appropriate benchmarks in the period from September 10, 2009 to November 17, 2009. The information ratio of 3.24 of the pair trading strategy is considerably higher than that of the two indices. Thus, using high-frequency sampling seems to offer significant improvement of the investment characteristics of the pair trading strategy. It offers a comparable absolute return to the one achieved by the Eurostoxx 50 index, with a significantly lower volatility.

Exhibit 19 displays, annualized trading statistics compared in the out-of-sample period for pair trading strategy sampled at the high-frequency interval, with the in-sample information ratio used as the indicator of the future profitability of the strategy

8. Concluding Remarks

In this article, we apply a pair trading strategy to the constituent shares of the Eurostoxx 50 index. We implement a basic long-short trading strategy, which is used to trade shares sampled at six different frequencies, namely data sampled at 5-minute, 10-minute, 20-minute, 30-minute, 60-minute, and daily intervals.

First, we divide shares into industry groups and form pairs of shares that belong to the same industry. The Kalman filter approach is used to calculate an adaptive beta for each pair.

Subsequently, we calculate the spread between the shares and simulate trading activity based on two simple trading rules. We enter the position (long or short) whenever the spread is more than 2 standard deviations away from its long-term mean. All positions are liquidated when the spread returns to its long-term mean (defined as its distance being less than 0.5 standard deviations from the long-term mean), that is, technically, when it reverts towards the long-term mean.

As such, standalone pair-trading results are not very attractive. That is why we introduce a novel approach to select the best pairs for trading based on the in-sample information ratio of the series, the in-sample t-stat of the ADF test of the series sampled at a daily interval, and a combination of the two, as these are shown to be good indicators of the out-of-sample profitability of the pair.

We then build a diversified pair trading portfolio based on the five trading pairs with the best in-sample indicator value. Our diversified approach is able to produce information ratios of over 3 for a high frequency sampling interval (an average across all the high-frequency intervals considered), and 1.3 for a daily sampling frequency, using the in-sample information ratio as an indicator. This is a very attractive result when compared to the performance of the Eurostoxx 50 index and the HFR Equity Market Neutral Index, with information ratios lower than 1 during the review period. It also illustrates how useful the combination of high-frequency data and the concept of cointegration can be for quantitative fund management.

Appendices

A. Kalman filter estimation procedure
The full specification of the model:

$$\beta_{t|t-1} = \beta_t$$
$$v_t = Y_t - X_t\beta_t$$
$$F_t = X_t P_t X'_t + H$$
$$\beta_{t+1} = \beta_t + P_t X'_t \frac{v_t}{F_t}$$
$$P_{t+1} = P_t - P_t X'_t X_t P_t \frac{1}{F_t} + Q$$

Exhibit A

The parameters that need to be set in advance are H and Q, which could be defined as the error terms of the process. Their values in isolation are not important. The most important parameter of the Kalman filter procedure is the noise ratio, which is defined as

$$noiseRatio = \frac{Q}{H}$$

The higher the ratio, the more adaptive beta and the lower the ratio, the less adaptive beta. Thus, if we used an extremely low value for the noise ratio, (e.g., 10^{-10}), the beta would be fixed along the dataset. Also, it is important to correctly initialize the value of beta, as in the second equation, $v_{t+1} = Y_t - X_t\beta_t$, there is no way of knowing what β_t will be at the first step. Thus, we have set β_1 to be:

$\beta_1 = \frac{Y_1}{X_1}$, thus the initial error term being 0.

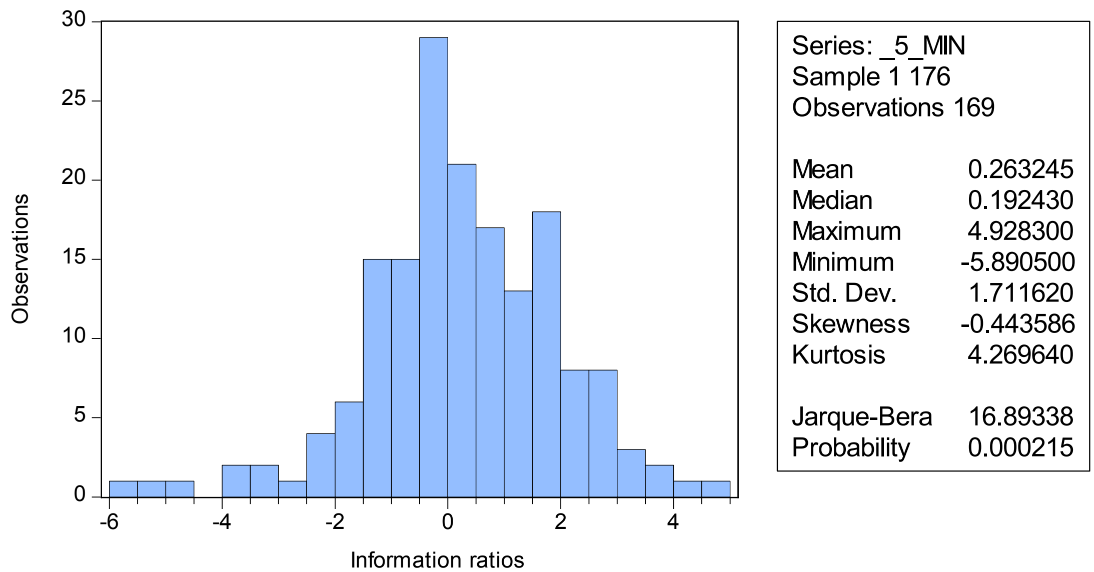

Exhibit B Distribution of information ratios for a 5-minute sampling frequency

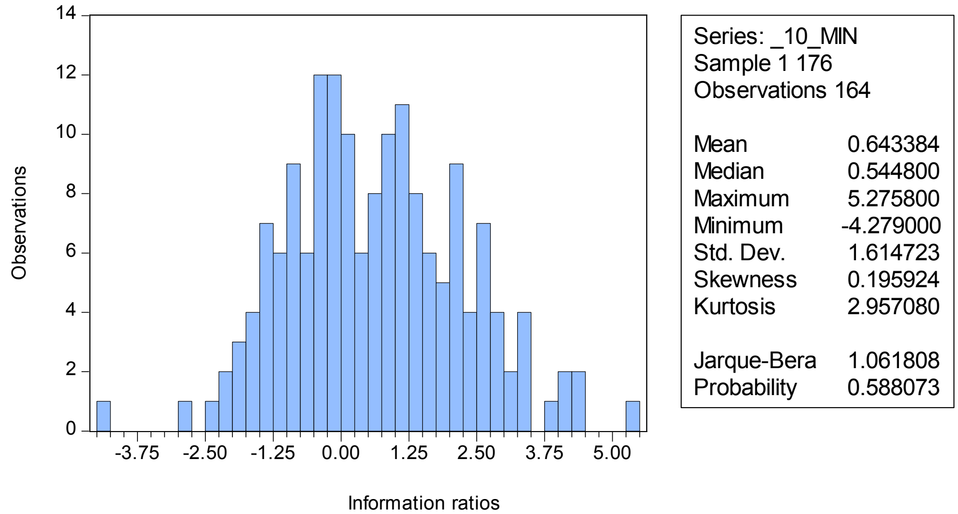

Exhibit C Distribution of information ratios for a 10-minute sampling frequency

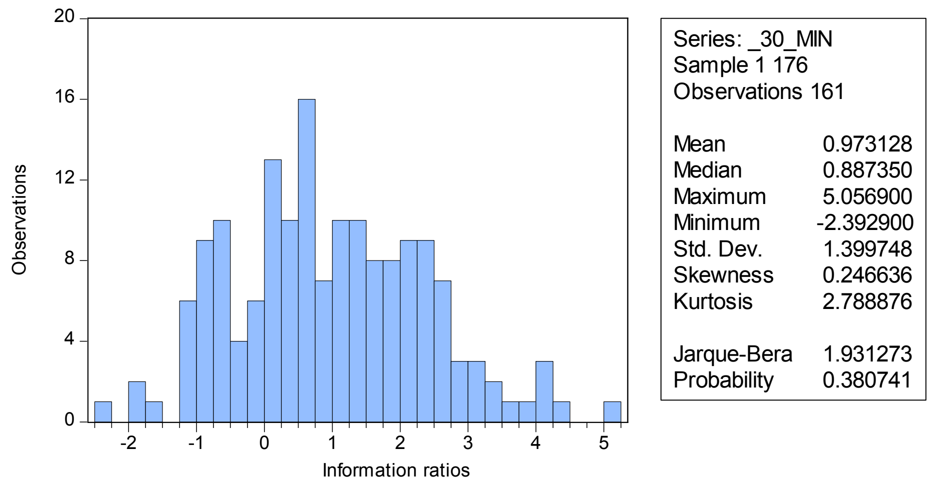

Exhibit D Distribution of information ratios for a 30-minute sampling frequency

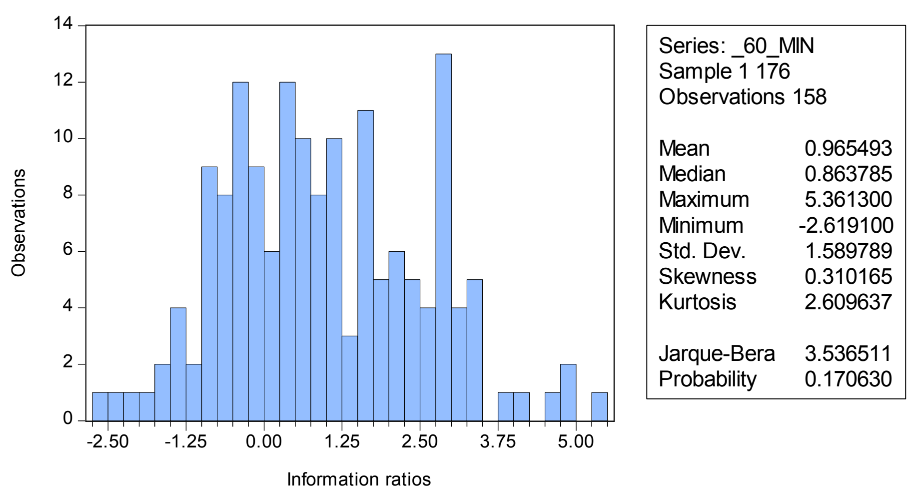

Exhibit E Distribution of information ratios for a 60-minute sampling frequency

Number	Company name	Bloomberg Ticker	Industrial sector
1	Air Liquide SA	AI FP Equity	Basic Materials
2	ArcelorMittal	MT NA Equity	Basic Materials
3	BASF SE	BAS GY Equity	Basic Materials
4	Bayer AG	BAYN GY Equity	Basic Materials
5	Deutsche Telekom AG	DTE GY Equity	Communications
6	France Telecom SA	FTE FP Equity	Communications
7	Nokia OYJ	NOK1V FH Equity	Communications
8	Telecom Italia SpA	TIT IM Equity	Communications
9	Telefonica SA	TEF SQ Equity	Communications
10	Vivendi SA	VIV FP Equity	Communications
11	Daimler AG	DAI GY Equity	Consumer, Cyclical
12	Volkswagen AG	VOW GY Equity	Consumer, Cyclical
13	Anheuser-Busch InBev NV	ABI BB Equity	Consumer, Non-cyclical
14	Carrefour SA	CA FP Equity	Consumer, Non-cyclical
15	Groupe Danone SA	BN FP Equity	Consumer, Non-cyclical
16	L'Oreal SA	OR FP Equity	Consumer, Non-cyclical
17	Sanofi-Aventis SA	SAN FP Equity	Consumer, Non-cyclical
18	Unilever NV	UNA NA Equity	Consumer, Non-cyclical
19	LVMH Moet Hennessy Louis Vuitton SA	MC FP Equity	Diversified
20	ENI SpA	ENI IM Equity	Energy
21	Repsol YPF SA	REP SQ Equity	Energy
22	Total SA	FP FP Equity	Energy
23	Aegon NV	AGN NA Equity	Financial
24	Allianz SE	ALV GY Equity	Financial
25	AXA SA	CS FP Equity	Financial
26	Banco Santander SA	SAN SQ Equity	Financial
27	Banco Bilbao Vizcaya Argentaria SA	BBVA SQ Equity	Financial
28	BNP Paribas	BNP FP Equity	Financial
29	Credit Agricole SA	ACA FP Equity	Financial
30	Deutsche Bank AG	DBK GY Equity	Financial
31	Deutsche Boerse AG	DB1 GY Equity	Financial
32	Assicurazioni Generali SpA	G IM Equity	Financial
33	ING Groep NV	INGA NA Equity	Financial
34	Intesa Sanpaolo SpA	ISP IM Equity	Financial
35	Muenchener Rueckversicherungs AG	MUV2 GY Equity	Financial
36	Societe Generale	GLE FP Equity	Financial
37	UniCredit SpA	UCG IM Equity	Financial
38	Alstom SA	ALO FP Equity	Industrial
39	CRH PLC	CRH ID Equity	Industrial
40	Koninklijke Philips Electronics NV	PHIA NA Equity	Industrial
41	Cie de Saint-Gobain	SGO FP Equity	Industrial
42	Schneider Electric SA	SU FP Equity	Industrial
43	Siemens AG	SIE GY Equity	Industrial
44	Vinci SA	DG FP Equity	Industrial
45	SAP AG	SAP GY Equity	Technology
46	E.ON AG	EOAN GY Equity	Utilities
47	Enel SpA	ENEL IM Equity	Utilities
48	GDF Suez	GSZ FP Equity	Utilities
49	Iberdrola SA	IBE SQ Equity	Utilities
50	RWE AG	RWE GY Equity	Utilities

Exhibit F Constituent stocks of Eurostoxx 50 index which were used to form the pairs Source: Bloomberg

Annualised Return	$R^A = 252 * \frac{1}{N}\sum_{t=1}^{N} R_t$ *with* R_t *being the daily return*
Annualised Volatility	$\sigma^A = \sqrt{252} * \sqrt{\frac{1}{N-1} * \sum_{t=1}^{N}\left(R_t - \overline{R}\right)^2}$
Information Ratio	$IR = \frac{R^A}{\sigma^A}$
Maximum Drawdown	*Maximum negative value of* $\sum(R_t)$ *over the period* $MD = \underset{i=1,\cdots,t;t=1,\cdots,N}{Min}\left(\sum_{j=i}^{t} R_j\right)$
Information Ratio	$SR = \frac{R^A - R_F}{\sigma^A}$, *where* R_F *is the risk free rate.*

Exhibit G. Calculation of the trading statistics

Endnotes

Sources for all figures are based on author's calculations, unless otherwise noted.

1 The information ratio is calculated as the ratio of annualized return to annualized standard deviation.

2 The high-frequency database includes prices of transactions for the shares that take place closest in time to the second 60 of particular minute-interval (e.g., transaction recorded just before the end of any 5-minute interval, or whichever selected interval in case of other high-frequencies), but not having taken place after second 60, so that if one transaction took place at 9:34:58 and the subsequent one at 9:35:01, the former transaction would be recorded as of 9:35. We download the data from Bloomberg, which only stores the last 100 business days of intraday data. We downloaded the data on November 17, 2009 and that is why our intraday data span from July 3, 2009.

3 Daily data are adjusted automatically by Bloomberg. Concerning intraday data, first we obtain the ratio of daily closing price (adjusted by Bloomberg) to the last intraday price for that day (representing the unadjusted closing price). Then we multiply all intraday data during that particular day by the calculated ratio. We repeat the procedure for all days and shares for which we have intraday data.

4 Daily data are automatically adjusted by Bloomberg.

5 Some shares do not date back as far as January 3, 2000, and as a consequence the pairs that they formed contain lower amount of data points In particular, four shares do not date back to January 3, 2000 (Anheuser-Busch starts on November 30, 2000, Credit Agricole S.A. starts on December 1, 2001, Deutsche Boerse AG starts on February 5, 2001 and GDF Suez starts on July 7, 2005).

6 If the out-of-sample period for daily data started at the same date as is the case for high-frequency data, it would not contain enough data points for the out-of-sample testing (had it started on September 10, it would have contained only as little as 50 observations and this is why we start the out-of-sample period for daily data at the beginning of 2009, yielding 229 data points).

7 The optimization was performed in MATLAB. The

genetic algorithm was run with default options. The optimization started with 100 generations and both mutation and crossover, were allowed.
8 We only optimized the parameters for 6 pairs, due to the length of the genetic optimization process.

9 The MATLAB function RAND was used to generate 6 random numbers from 1 to 176 (as RAND only generates numbers from 0 to 1, the result of RAND was multiplied by 176 and rounded to the nearest integer towards infinity with the function ceil). 176 is the number of all the possible pairs out of 50 shares, provided that only the pairs of shares from the same industry are selected.

10 Above we explained that our positions are money neutral on both sides of the trade. However, in practice this is not always possible, as an investor is not able to buy share fractions. Thus, it might occur that we wish to be long 1,000 euros worth of share A and short 1,000 euros worth of share B. But the price of share X is 35 euros and the price of share Y is 100 euros. In this case we would need to buy 28.57 shares of X and sell 10 shares of Y. In the paper we simplified the issue and supposed that an investor is able to buy fractions of the shares. The reason is that one is able to get as close as one wishes to the money neutral position in practice. The only thing one has to do is to increase the amount of money on both sides of the trade. If in the previous example we wished to be long and short 100,000 euros, we would buy 2,857 shares X and 1,000 shares Y.

11 We do not know which of the cases will occur in advance: whether the shares return to their long term equilibrium, because the overvalued share falls more, the undervalued rises more, or both perform the same.

12 The pair was chosen only for an illustration of the approach. Both shares are from the same industry: basic materials, see Appendix E. In Figure 2 the same pair of shares is shown as was the case in Figure 1.

13 IR has now become more popular among practitioners in quantitative finance than Sharpe ratio. The formula for a Sharpe ratio (SR) calculation can be found in Appendix G. Note that the only difference between IR and SR is the risk free rate in the denominator of SR.

14 For instance Interactive Brokers charges 0.1% per transaction on XETRA market (http://www.interactivebrokers.com/en/p.php?f=commission and http://www.interactivebrokers.com/en/accounts/fees/euroStockBundlUnbund.php?ib_entity=llc, the bundled cost structure. Last accessed February 14, 2010)

15 Our objective is to analyze the relation between the t-stat and the information ratio for all the pairs. Instead of calculating a point estimate of a correlation coefficient, we prefer to calculate the confidence intervals of a true correlation coefficient. We perform bootstrapping with replacement, the standard computer-intensive technique used in statistical inference to find confidence intervals of an estimated variable (e.g., Efron, B. and Tibshirani, R. J. (1993)). It is a quantitative process in which we randomly repeat the selection of data (we repeat it for 5,000 times). Some samples might contain the same item more than once (hence the bootstrapping with replacement), whereas others may not be included at all. The process provides a new set of samples which is then used to calculate the unbiased confidence intervals for the true correlation coefficient. Bootstrapping in our case is a simple process of creating 5,000 random samples from the original data set in such a way, that the corresponding pairs are selected 176 times from an original data set to form each of 5000 samples.

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The Resiliency of the U.S. Futures Industry

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1. Introduction

Financial professionals are well-aware that the ongoing implementation of the Dodd-Frank Act could cause changes to market structure, including the structure of the futures markets. Should market participants be concerned? The short answer is not necessarily, given that the history of U.S. futures trading is one of responding to constant adversity through dynamic innovation.

2. How and Why U.S. Futures Trading Began

The story of U.S. futures markets has largely been one of innovation flowing from Chicago, with additional innovations taking place elsewhere. Chicago became a transportation hub and grain terminal in the mid-nineteenth century and, as its scale and influence grew, grain merchants had to figure out how to manage the price risk for their accumulating volume of grain inventories. The solution was the development of a formalized exchange: the Chicago Board of Trade (CBOT).

At the time, Chicago was already a well-established center of financial risk-taking, due to the land speculation that had occurred in Illinois in the 1830s prompted by the building of a significant canal that linked Illinois's productive farmland to major population centers. Exhibit 1 reproduces a historical painting of another seminal occasion in Chicago's commercial history: the establishment of the first grain elevator in 1838.

In a pattern that would repeat itself, the Chicago Board of Trade's founding was the "result of evolution, not intent or design," noted Stassen (1982), who explained, "The Chicago Board of Trade was created by businessmen as a commercial exchange for businessmen – grain merchants – who needed some order in a world of chaos, and some relief from a hostile judicial system which only reluctantly enforced businessmen's bargains…
[T]he courts in Illinois, as in most states, adhered to old English precedent, which places damages for expected profits on a par with usury."

In spite of their illustrious history, grain merchants in Chicago were not the originators of futures trading. According to Teweles and Jones (1974), the first recorded case of organized futures trading occurred in Japan during the 1600s in the rice markets. Hieronymous (1971) went back even further, noting, "The concept of futurity in contractual arrangements is as old as commerce. The rules of futures trading certainly date back to the medieval fairs of France and England, which were large and complex by the 12th Century."…"[B]ut as a practical matter, we need look no further back than the frontier of the U.S. in the mid-19th century for the origin of modern futures trading." [Italics added.] "The circumstances of the frontier, particularly in the grain trade, were the catalyzing agent out of which futures trading grew."

In describing the business conditions of the mid-

Exhibit 1 "The First Grain Elevator in Chicago, 1838" Postcard of a 1902 Painting By Lawrence C. Earle
Source: http://www.lcearle.com/works/CH-grainelevator-1838.jpg, retrieved on October 19, 2013.
Note: This 1902 painting is "one of 16 historical paintings by Lawrence C. Earle, [which were] originally located in the banking room of the Central Trust Company of Illinois, 152 Monroe Street, Chicago;" the paintings are "now stored within the Collection Services Department at the Chicago History Museum," according to http://www.earlychicago.com. This website, in turn, is based on Danckers and Meredith (1999).

nineteenth century, Hieronymous quoted Emery (1896), "Untrammeled by business traditions of past centuries … the trade of this country has unconsciously adopted new and direct means for attaining its ends. There has been little 'history' or 'evolution' about the process, for the practical mind of the business man has simply seized the most direct method of 'facilitating' business, a course forced on him by the constantly increasing size of transactions."

With hindsight, we know that Chicago's century-plus heritage of financial risk-taking came to serve the city well. For example, Chicago futures traders responded to the dislocations that were caused by the collapse of the Bretton Woods system of fixed exchange rates successfully. Spurred on by changes in the currency markets, the Chicago exchanges developed financial hedging instruments in both currencies and interest rates in the 1970s and 1980s.

The launch of financial futures trading in Chicago became hugely successful and it is surprising to read about the early skepticism that greeted these efforts, as discussed by Leo Melamed, Chairman Emeritus of the Chicago Mercantile Exchange (CME) Group, Inc. According to Melamed (1994), "Some … thought it ludicrous that [in the early 1970s] a 'bunch of pork belly crapshooters' would dare" launch futures contracts on foreign exchange." Former CME Chairman Jack Sandner would later proudly explain, "Financial futures were spawned out of the belly of the hog," cited in Baeckelandt (2012).

3. How the Futures Exchanges Were Forced to Innovate Constantly

The maxim, "with crisis comes opportunity," has been a constant for the Chicago futures exchanges and predates the collapse of the Bretton Woods system. For example, in the 1960s, the CME had to develop new futures contracts because its mainstay futures contracts in eggs and butter had become obsolete. Technological changes had transformed the production, distribution, and storage of butter and eggs from seasonally produced commodities with classical production and price cycles to new and different products with regard to their production, price, and distribution patterns. "The economic necessity of hedging provided by a futures market had greatly diminished," recalled Everette Harris, the former president of the CME, in Harris (1970).

What was the response of the futures industry to this crisis? The answer was: "innovation." Starting in the early 1960s, the CME began introducing livestock futures contracts. By 1980, the live cattle futures contract had become the largest contract on the exchange according to a speech made by Leo Melamed at the time.

Admittedly, Chicago has not been the only center of innovation in U.S. futures market development. In the 1970s, the New York Mercantile Exchange (NYMEX) had faced possible extinction when its mainstay contract, the Maine potato, lost credibility during scandals in 1976 and 1979. Fortuitously, the NYMEX responded to an emerging opportunity instead. The structure of the oil industry had changed after numerous nationalizations of firms in oil-producing countries. This forced some oil companies to shift from long-term contracts to the spot oil market, according to Pulitzer Prize winner, Daniel Yergin, in his book, The Prize.

Verleger (2012) added that the U.K. government's taxation of North Sea oil contributed to the development of spot oil markets. "[T]he U.K. Treasury granted itself the right to decide the value of any oil processed by the company that produced it. Exxon, for example, would have been at the mercy of U.K. tax authorities had it processed crude from its fields. Rather than take such a risk, producers chose to sell their crude and then buy crude for processing from others. Their transactions created the first observable spot market for crude."

With the structure of the oil industry changing, an economic need for hedging volatile spot oil price risk emerged and the NYMEX responded to the opportunity with a suite of energy futures contracts, starting with the heating oil contract in 1981.

According to Yergin (1992), "The initial reaction to the futures market on the part of the established oil companies was one of skepticism and outright hostility. … A senior executive of one of the … [major oil companies] dismissed oil futures 'as a way for dentists to lose money.' But the practice … [of] futures [trading] … moved quickly in terms of acceptability and respectability. … Price risk being what it was, … no [commercial entity] … could afford to stay out. As the volume of transactions built up astronomically, Maine potatoes became a distant … and embarrassing memory" at the NYMEX.

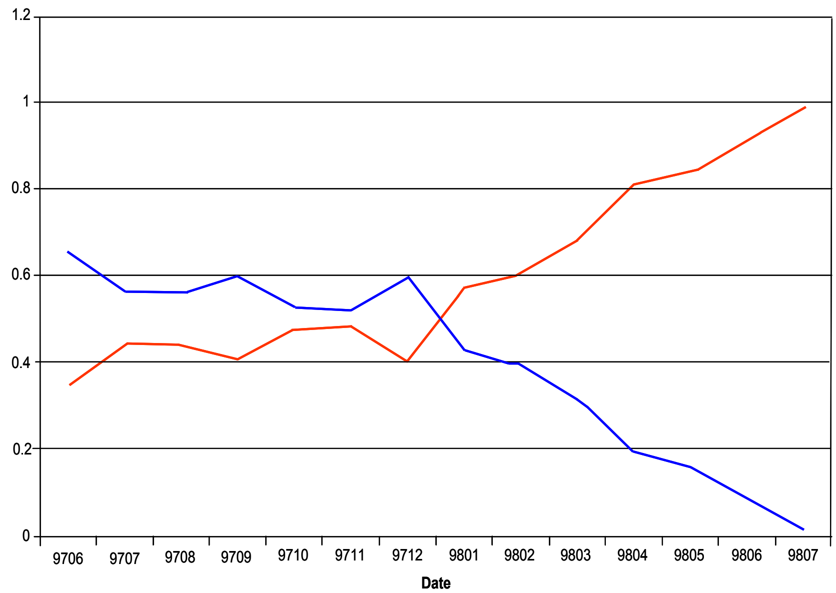

Exhibit 2 Eurex/DTB and LIFFE Bund Market Shares
Source: Pirrong (2005), Figure 1.
Note: The blue line is LIFFE's market share while the red line shows the Eurex/DTB's market share.

Later, new challenges confronted the established U.S. exchanges. The CBOT, CME, and NYMEX were facing competitive threats from new forms of electronic trading. The starkest example came from Europe in 1998. At that time, the electronic exchange, the EUREX (DTB), successfully wrestled control of the 10-year German government bond futures contract, the Bund contract, from the (then) open-outcry LIFFE exchange in London by waging a "price war on fees." Exhibit 2 illustrates how quickly LIFFE lost market share during this battle.

This unprecedented victory of an all-electronic venue over an established exchange accelerated the pace of change in Chicago. Soon after the Eurex coup, both the CBOT and CME embraced concurrent open-outcry and electronic trading. Under pressure from ICE Futures Europe, another innovative electronic futures exchange, the NYMEX listed its energy futures contracts on the CME's Globex electronic trading system in 2006.

In the late 1990s, worries about Chicago's competitiveness in the international arena continued unabated. According to Melamed (2009), "the only way to prepare … [the CME] for the twenty-first century" was to demutualize; a member-driven organization was too slow in its decision-making processes. The result could be that the CME would lose the first-mover advantage that resulted from taking advantage of expected disruptive changes that were being stimulated by globalization and technological change. Therefore, the CME went public in 2002, becoming the first U.S. financial exchange that was itself traded in the public markets..

By 2006, the Chicago Mercantile Exchange's trading volume "exceeded 2.2 billion contracts – worth more than $1,000 trillion – with three-quarters of … trades executed electronically," according to CME (2007). In 2007, the CBOT merged with its historic cross-town rival CME; and in 2008, the NYMEX was merged into the combined Chicago exchange, CME Group, Inc.

Confirming Melamed's concern on how competitive the global environment could become, Acworth (2012) reported that as of 2011, two-thirds of all futures volume was being traded outside the United States, as illustrated in Exhibit 3.

4. Adversity Has Always Been an Essential Part of the Story

Given the dramatic narrative above, it is clear that adversity is an essential part of the story concerning the evolution of the futures industry. After all, adversity is the story of trading itself. As experts and market participants know, trading "requires discipline to tolerate and endure emotional pain to a level that 19 out of 20 people cannot bear. … Anyone who claims

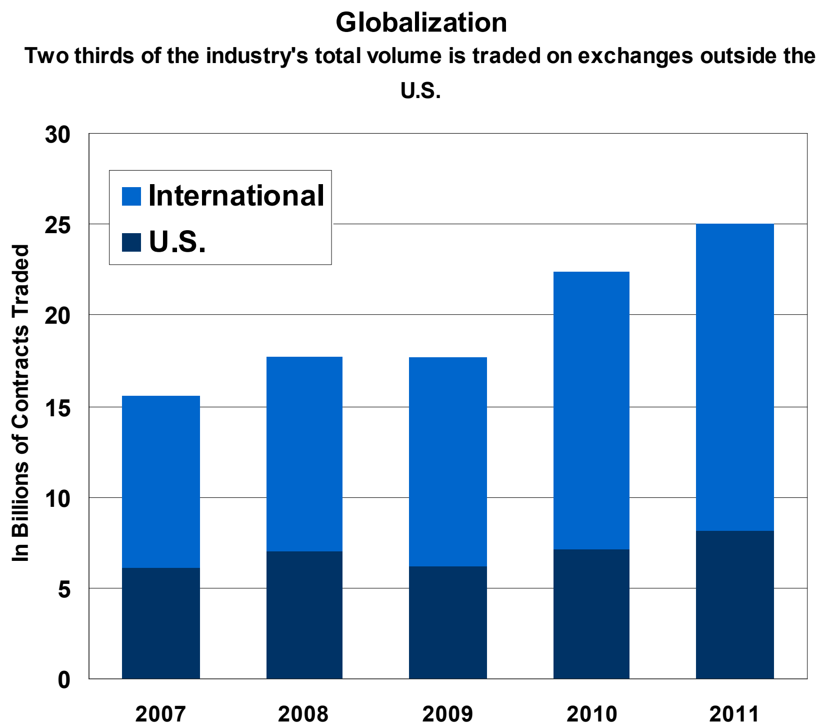

Exhibit 3
Source: Acworth (2012).

to be intrigued by the 'intellectual challenge of the markets is not a trader. The markets are as intellectually challenging as a fistfight. … Ultimately, trading is an exercise in self-mastery and endurance," as noted in Vince (1992). The same may be said about product development in the futures markets, where the history is largely one of overcoming failure and skepticism.

In 1953, the eminent empirical economist Holbrook Working began distilling lessons from past futures contract failures. In Working (1953), for example, he discussed why past efforts to "provide good hedging facilities for Pacific Northwest wheat" had invariably failed.

As shown in Exhibit 4, Chicago wheat futures prices exhibited extreme changes when the Portland wheat spot price also exhibited extreme changes. This meant that Chicago wheat futures contracts could have plausibly protected commercials that had exposure to Portland wheat prices, albeit imperfectly.

Given that Chicago wheat futures contracts were very liquid, the cost of entering and exiting Chicago wheat contracts was small enough to make the cost of this type of "insurance" sufficiently small as to make Chicago wheat futures contracts attractive to these commercial market participants. This, in turn, meant that illiquid contracts specifically designed for the Portland, and other Pacific Northwest wheat markets had trouble attracting enough business to succeed.

Later in 1970, Working summarized the four conditions "necessary for a futures market to survive and prosper." These hard-won lessons are still relevant today:

1. The contract terms and commission charges must be such as to attract appreciable use of the futures contract for merchandising purposes.
2. There must exist a possibility of attracting enough speculation to provide at least a reasonably fluid market.
3. Handlers of the commodity must have reasons to make substantial use of the futures contracts as temporary substitutes for merchandising contracts that they will make later.
4. There must exist adequate public recognition of the economic usefulness of the futures market.

Furthermore, an enduring philosophy of the CME has been an acceptance of the possibility of failure in its new product ventures: "Necessity is the mother of invention.

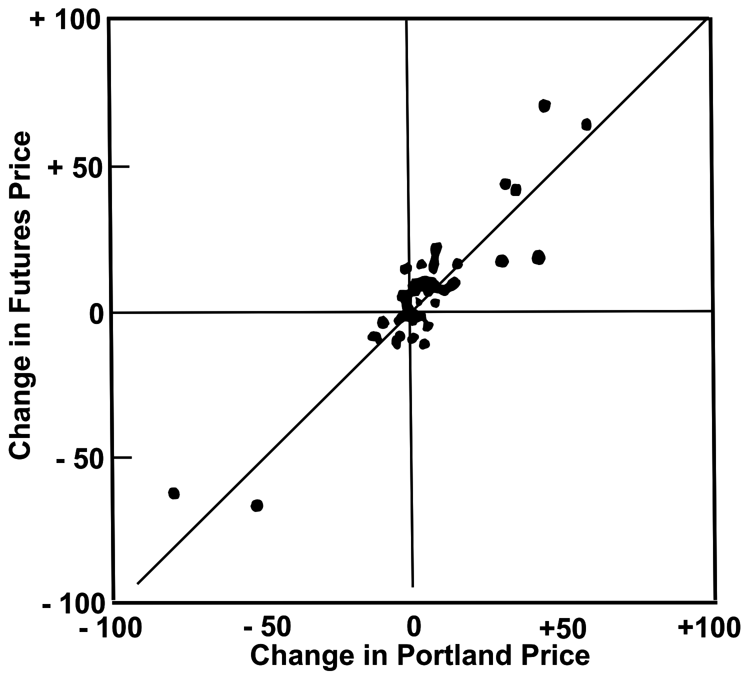

Exhibit 4 Relations of Two-Month Changes in Prices of Chicago Wheat Futures to Simultaneous Changes in Portland Spot Prices September 1946 to May 1952
Source: Excerpted from Working (1953), Chart 1.

Beginning in the early fifties … [CME] members have vigorously researched, tested, and promoted many new contracts for futures trading. … Some have succeeded and some have failed, but fear of failure has not impeded progress," noted Harris (1970).

Conclusion

In reviewing the history of U.S. futures markets, one gets a sense of the resiliency of these institutions, in constantly responding to adversity from their earliest days and well into the modern times. Based on this history, one would expect that resiliency to continue, not through some "designing intelligence," but rather through a willingness to continue to innovate through trial-and-error efforts. This insight may be one of the most important lessons for new and emerging financial centers as well.

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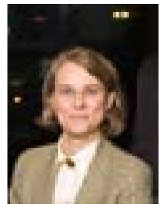

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IR&M Momentum Monitor

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Ineichen Research & Management AG

1. Introducing MOM

Spotting change is important. There are essentially two approaches to change: having a guess, or measuring it in a systematic fashion with an applicable methodology. The latter is robust, the former is not. Momentum can be perceived as a philosophy. We herein recommend it as a risk management tool, rather than a philosophy. If risk is defined as "exposure to change," then one ought to spot the change.

2. Purpose

The aim of this article is to add some color to the IR&M Momentum Monitor (MOM). MOM seeks to improve the investor's investment decisions. The idea behind monitoring prices and earnings (or anything else) is twofold: observation and discipline. A monitor allows regularly observing as well as regularly revisiting large amounts of data in a systematic fashion. MOM can also add discipline to an investment process. MOM's "signal" is systematic—essentially the opposite of someone's forecast.

The idea is not to forecast the future, but to assess the present and decide whether an investment is in a favorable environment or an unfavorable one. Essentially deciding, literally, whether it's green for "go" or red for "don't go". MOM's thumb is either up or down, so to speak.

3. Momentum as a Risk Measure

Risk management is the main task of the absolute returns investor. It is losses, especially large ones that kill the rate at which capital compounds. It is the drawdown measure that is important, not volatility. Volatility by itself can be a good thing. Equities are more volatile than bonds and outperform bonds most of the time. Volatility can be both good and bad, while drawdowns are unambiguously bad.

The MOM was designed to assist risk takers and investment managers in their risk management. It provides signals that can initiate a thought process. The MOM is not the Holy Grail of finance, unfortunately. However, it is designed to quite literally spot change. If risk is defined "exposure to change," then pointing it out seems important and relevant. MOM spots change systematically. The advantage is that MOM signals when the environment changes from headwind to tailwind or vice versa reasonably early and in a systematic fashion. One therefore ought to listen to MOM. The factual knowledge should then help improve decision making. It can help with tactical asset allocation, position sizing, allocating new funds, hedging, and other facets of the investment process.

The Momentum idea can also be applied to earnings estimates. Earnings estimates by themselves are forecasts. An earnings estimate might or might not turn out to be correct. It's a forecast. However, the trend in consensus earnings forecasts is a fact, not a forecast. It can be measured objectively. Relying on facts that can be measured objectively adds to the robustness of the investment decision-making process.

4. Bottom Line

Change matters much more than the current state of things. Stocks in Russia, India, and China are trading at single digit private equity (PE) ratios. That's a fact, it's the status quo. However, it could well be that in three, four, or five years these stocks will still be trading at single digit PEs; who knows? We believe change to be more important; hence the focus on momentum. Misusing Newton's laws, it means a catalyst is required to move from a static state to a dynamic one. Predicting these catalysts - the butterfly wing flaps that can set of tornadoes - is difficult. Preferably, one ought to focus on movements where the catalyst has already occurred, (i.e., where the motion is already taking place). Hence the focus on measured change and motion, rather than status quo, that might or might not change soon. MOM can do all that.

IR&M Momentum Monitor

By Alexander Ineichen, CFA, CAIA, FRM; www.ineichen-rm.com

March 2014

Calendar Week	Price Momentum: Medium-term 7	8	9	10	Price Momentum: Long-term 7	8	9	10	Earnings Momentum: Medium-term 7	8	9	10	Earnings Momentum: Long-term 7	8	9	10
Equities by region																
MSCI World	1	2	3	4	79	80	81	82	8	9	10	11	54	55	56	57
Europe (STOXX 600)	9	10	11	12	80	81	82	83	-1	-2	-3	-4	4	5	-1	-2
MSCI Emerging Markets	-10	-11	-12	-13	-3	-4	-5	-6	-5	-6	-7	-8	-33	-34	-35	-36
MSCI Asia Pacific ex Japan	-10	-11	1	2	-1	1	2	3	-12	-13	-14	1	15	16	17	18
Equities by country																
USA (S&P 500)	1	2	3	4	108	109	110	111	63	64	65	66	102	103	104	105
Canada (SPTSX 60)	31	32	33	34	25	26	27	28	8	9	10	11	16	-1	-2	-3
Brazil (Bovespa)	-13	-14	-15	-16	-7	-8	-9	-10	16	17	18	-1	9	10	11	12
France (CAC 40)	1	2	3	4	79	80	81	82	-4	-5	-6	-7	-126	-127	-128	-129
Germany (DAX 30)	32	33	34	35	81	82	83	84	1	2	3	4	43	44	45	46
Italy (FTSE MIB)	8	9	10	11	25	26	27	28	6	-1	-2	-3	3	4	5	6
Switzerland (SMI)	8	9	10	11	63	64	65	66	-2	-3	-4	-5	-4	-5	-6	-7
UK (FTSE100)	-3	1	2	3	79	80	81	82	-30	-31	-32	-33	-24	-25	-26	-27
Australia (S&P/ASX)	1	2	3	4	77	78	79	80	17	18	19	20	45	46	47	48
China (Shanghai Composite)	-9	1	-1	-2	-6	-7	-8	-9	12	13	14	15	49	50	51	52
Hong Kong (Hang Seng)	-9	-10	1	2	21	22	23	24	74	75	-1	-2	65	66	67	68
India (Nifty)	-3	-4	1	2	17	18	19	20	21	22	23	24	105	106	107	108
Japan (Nikkei 225)	-3	-4	-5	-6	62	63	64	65	13	14	15	16	51	52	53	54
South Korea (Kospi)	-10	-11	1	2	19	-1	-2	-3	-6	-7	-8	-9	-36	-37	-38	-39
Bonds																
Barclays Global Aggregate	5	6	7	8	16	17	18	19								
Barclays Global HY	23	24	25	26	24	25	26	27								
Barclays Euro Aggregate	21	22	23	24	16	17	18	19								
Barclays Asia Pacific Aggregate	23	24	25	26	19	20	21	22								
Barclays Global Emerging Markets	2	3	4	5	10	11	12	13								
Barclays US Aggregate	6	7	8	9	5	6	7	8								
Barclays US Corporate HY	23	24	25	26	112	113	114	115								
Hedge Funds																
HFRX Global Hedge Funds	23	24	25	26	77	78	79	80								
HFRX Macro/CTA	-2	-3	-4	-5	-34	-35	-36	-37								
HFRX Equity Hedge	22	23	24	25	77	78	79	80								
HFRX Event Driven	64	65	66	67	76	77	78	79								
HFRX Relative Value Arbitrage	23	24	25	26	14	15	16	17								
HFRX Fixed Income - Credit	85	86	87	88	147	148	149	150								
Commodities																
Thomson Reuters/Jefferies CRB	4	5	6	7	-50	1	2	3								
Gold (Comex)	2	3	4	5	-63	-64	-65	-66								
Copper (Comex)	-3	-4	-5	-6	9	10	11	12								
Oil (WTI)	3	4	5	6	-12	-13	-14	-15								
FX																
USD (trade-weighted, DXY)	-1	-2	-3	-4	-22	-23	-24	-25								
EURUSD	1	2	3	4	30	31	32	33								
JPYUSD	3	4	5	-1	-64	-65	-66	-67								
Central banks' balance sheets																
Fed balance sheet	70	71	72	73	62	63	64	65								
ECB balance sheet	-12	-13	-14	-15	-61	-62	-63	-64								
BoJ balance sheet	93	94	95	96	147	148	149	150								
BoE balance sheet	2	3	4	5	-41	-42	-43	-44								

Commentary

Most equity markets shown here are in a long-term bull market. Emerging markets turned negative in late 2013.

Earnings momentum for the MSCI World and S&P 500 has been positive for a while.

Momentum in bonds is mostly positive.

Momentum in hedge funds has been positive for more than a year.

Commodities have turned and are now rising.

The Fed's balance sheet is expanding merrily.

Tutorial

The momentum numbers count the weeks of a trend based on moving averages. Green marks a positive trend, red a negative one. Example: In week 49, the S&P has been in a long-term bullish trend for 98 weeks. See www.ineichen-rm.com for more information and/or trial issue.

Purpose

The momentum monitor was designed to help investors with risk management, asset allocation, and position sizing. Tail events do not always happen out of the blue. They often occur when momentum is negative. Negative momentum makes hedging more important and suggests position sizing should be more conservative. In a bull market one ought to be long or flat but not short. In a bear market one ought to be short or flat but not long.

Source: IR&M, Bloomberg. Notes: Medium-term based on exponentially weighted average over 3 and 10 weeks. Long-term based on simply weighted average over 10 and 40 weeks. Earnings momentum is based on 12-month forward concesus EPS estimates.

Author Bio

Alexander Ineichen is founder of Ineichen Research and Management AG, a research firm founded in October 2009 focusing on risk management, absolute returns, and thematic investing.

Alexander started his financial career in derivatives brokerage and origination of risk management products at Swiss Bank Corporation in 1988. From 1991 to 2005 he had various research functions within UBS Investment Bank in Zurich and London relating to equity derivatives, indices, capital flows, and alternative investments, since 2002 in the role of a Managing Director. From 2005 to 2008, he was a Senior Investment Officer with Alternative Investment Solutions, a fund of hedge funds within UBS Global Asset Management. In 2009, he was Head of Industry Research for the hedge fund platform at UBS Global Asset Management.

Alexander is the author of the two publications "In Search of Alpha: Investing in Hedge Funds" (October 2000) and "The Search for Alpha Continues: Do Fund of Hedge Funds Add Value?" (September 2001). These two documents were the most-often printed research publications in the documented history of UBS. He is also author of "Absolute Returns: The Risk and Opportunities of Hedge Fund Investing" (Wiley Finance, October 2002) and "Asymmetric Returns: The Future of Active Asset Management" (Wiley Finance, November 2006). Alexander has also written several research pieces pertaining to equity derivatives and hedge funds including AIMA's Roadmap to Hedge Funds (2008 and 2012), which has been translated into Chinese and was the most-often downloaded document from their website at the time.

Alexander holds a Bachelor of Science in Business Administration with Major in General Management from the University of Applied Sciences in Business Administration Zürich (HWZ) in Switzerland. Alexander also holds the Chartered Financial Analyst (CFA) and Chartered Alternative Investment Analyst (CAIA) designations and is a certified Financial Risk Manager (FRM). He is on the Board of Directors of the CAIA Association and is a member of the AIMA Research Committee.

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