12TH ANNUAL GLOBAL ETF AWARDS®

"How the industry measures excellence."

April 21, 2016
New York Grand Hyatt, New York
Workshop & Dinner Program

Table of Contents

Sponsors of the 12th Annual ETF Global Awards© include:

LEAD SPONSOR

BNY MELLON

BNY Mellon is a global investments company dedicated to helping its clients manage and service their financial assets throughout the investment lifecycle. Whether providing financial services for institutions, corporations or individual investors, BNY Mellon delivers informed investment management and investment services in 35 countries and more than 100 markets. As of Dec. 31, 2015, BNY Mellon had $28.9 trillion in assets under custody and/or administration, and $1.6 trillion in assets under management. BNY Mellon can act as a single point of contact for clients looking to create, trade, hold, manage, service, distribute or restructure investments. BNY Mellon is the corporate brand of The Bank of New York Mellon Corporation (NYSE: BK).

Additional information is available on www.bnymellon.com/newsroom.

Exclusive Cocktail Reception Sponsor

STOXX Ltd. is an established and leading index specialist, which started in Europe. The launch of the first STOXX® indices in 1998, including the EURO STOXX 50® Index, marked the beginning of a unique success story, based on the company's neutrality and independence. Since then, STOXX has been at the forefront of market developments and has continuously expanded its portfolio of innovative indices. STOXX now operates globally across all asset classes.

STOXX indices are licensed to more than 500 companies, which include the world's largest financial products issuers, capital owners and asset managers. STOXX indices are used not only as underlyings for financial products, such as ETFs, futures and options and structured products but also for risk and performance measurement.
In addition, STOXX Ltd. is the marketing agent for DAX® indices.

For more information, please visit www.stoxx.com.

Platinum sponsors

FLOW TRADERS

Flow Traders is an independent ETF & ETC market maker with major trading operations in Europe, Asia and the US. With a team of over 230 professionals globally; 65 traders and 76 employees focused on proprietary IT and development, we provide continuous liquidity for ETFs & ETCs on all major exchanges world-wide.

Our 11 dedicated Sales Traders in Amsterdam and Singapore provide institutional investors with highly competitive bid offer prices on an OTC basis for ETFs & ETCs from all issuers, all asset classes, and all global exchanges, including pre-open and post-close hours.

Flow Traders has been voted as the number one European ETF Market Maker by industry participants via the Global ETF Awards consecutively each year since 2007 and ETF Market Maker Asia-Pacific in 2011, 2012 and 2013.

ISE International Securities Exchange. ETF VENTURES

The ISE ETF Ventures team is dedicated to creating and supporting innovative indexes that track growing industries, emerging technologies and markets, and packaged trading strategies.

Their index design expertise includes a diverse range of asset classes and instrument types including global equities, fixed income, currencies, futures and options. ISE ETF Ventures partners with issuers to launch unique exchange traded products (ETPs) such as exchange traded funds (ETFs), exchange traded notes (ETNs), and other similar product types.

They also provide capital for the start-up and ongoing backstopping of new ETPs. Partners are able to leverage ISE ETF Ventures' global experience and broad network of industry participants in order to grow their ETP presence as well as reduce risk and increase product issuance. Total assets under management for ETPs tied to ISE ETF Ventures is approximately $3 billion.

GOLD SPONSOR

U.S. Bancorp Fund Services, LLC has been providing seamless administration services to a diverse client base since 1969. Our dedicated ETF team supports active and passive ETFs, including fixed income and equity, inverse, leveraged, derivativebased, and commodity funds. Additionally, we offer a full suite of services for NextShares ETPs. Our network and fully integrated ETF technology resources are standing by to help keep you connected.

To learn more about our comprehensive ETF solutions, please visit http://www.usbfs.com/.

Dinner Table Sponsors

Site Sponsor

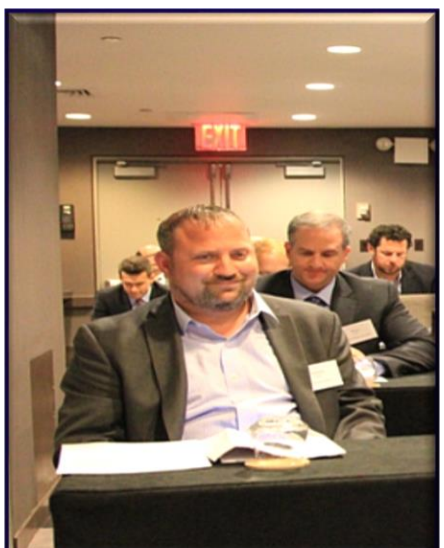
2:00 PM-Maximizing returns with Smart Beta and Actively-managed ETFs

Moderator:
Danielle K. Jarnot,
Vice President,
Institutional Sales, Aqua

Panelists:
Kathy Cuocolo, CPA,
President, Syntax LLC

Jay Jacobs CFA
Director of Research,
Global X

Rowland O. Wilhelm, Jr.
Vice President, Director of
Marketing and Sales
Reaves Asset Management



2:45 PM-Managing Volatility-The Saga Continues

Moderator:
Mike Venuto, Chief Investment Officer, TOROSO INVESTMENTS

Panelists:
Jay Caauwe, Managing Director, Global Client Services, CBOE HOLDINGS

Kevin Kelly, Managing Partner, RECON CAPITAL PARTNERS

Corey Villani, Senior Product Development Specialist, ISE ETF VENTURES

2:45PM- Market Makers- Smart Trades, Better Executions

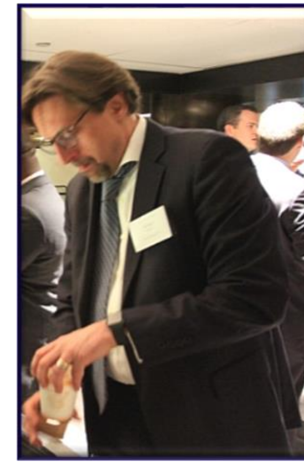
Moderator:
Richard Keary,
Principal/Founder,
Global ETF Advisors, LLC

Panelists:
Chris Hempstead,
Head of ETF Sales, KCG

Christopher Johnson,
Vice President,
Americas – ETF Sales,
MACQUARIE
CAPITAL (USA) INC.

Maarten van den
Muijsenberg, Head of
Trading at Flow Traders US

3:30 PM-Refreshment Break






3:45 PM-Finding a Unicorn-Liquidity in Fixed Income ETFs

Moderator:
Mike Castino, Senior Vice President, U.S. BANCORP FUND SERVICES, LLC

Panelists:
Bryce A. Doty, CFA, Senior VP-Senior Fixed Income Manager, SIT INVESTMENT ASSOCIATES

Stefano Pasquali, Head of Liquidity Research, Regulatory & Accounting Products BLOOMBERG, LP

Kelly Westfall, Director, Financial Services O'CONNOR DAVIES, LLP

3:45 PM-Searching for Opportunities in Emerging Markets and Commodities

Moderator:
Thomas O'Donnell, Managing Director, ETF Client Service Management Team, BNY Mellon

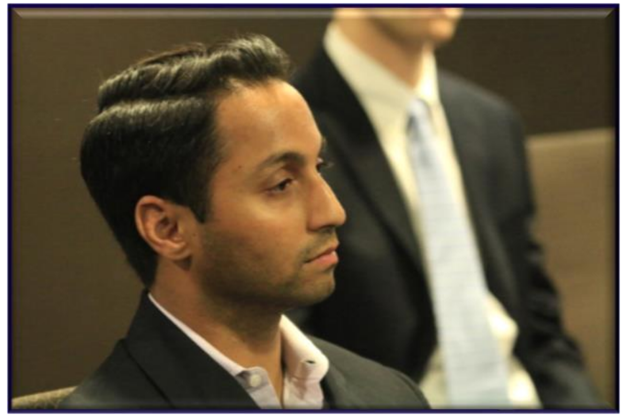
Panelists:
Mike McGlone, MCGLONE ADVISORS LLC

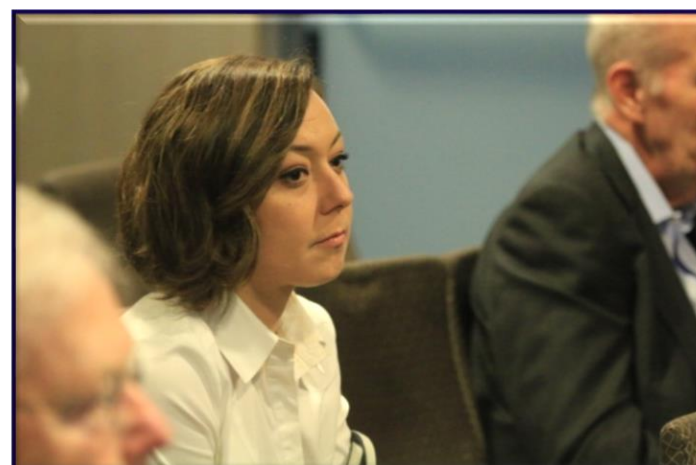
A. Seddik Meziani, Ph. D, Professor of Economics and Finance, MONTCLAIR STATE UNIVERSITY and Author

Steven Schoenfeld, Bluestar Global Investors LLC


SCHOENFELD
MEZIANI


MCGLONE

4:30 PM-Insights into Indexing

Moderator:
Robert Tull , ROBERT TULL AND COMPANY

Panelists:
Tom Goodwin, PhD,
Senior Research Director,
FTSE Russell Indexes

Rod Jones, Head of North America, STOXX

Joseph Halpern,
Exceed Investments,
Founder and CEO

Robert Michaud,
Chief Investment
Officer, New Frontier


JONES
GOODWIN
AQUAFINA

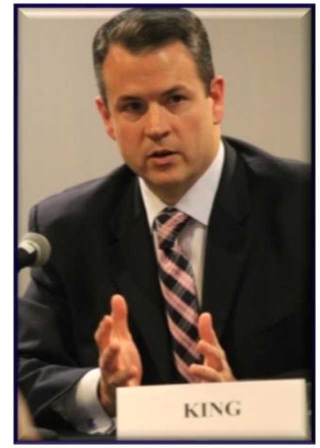

HALPERN
AQUAFINA


MICHAUD
HALPERN

5:15 PM-Looking into the Future of the Global ETP Marketplace

Moderator:
Andrew Pfeifer,,
Relationship Executive,
BNY MELLON

Panelists:
David Abner, Director, Head of Capital Markets, WisdomTree Asset Management, Inc



Brian King, Director of ETP Listings, NYSE

Phil Nanof, ETF Product Specialist, State Street Global Services

Dodd Kittsley, CFA, Director, Head of ETF Strategy & National Accounts, DEAWM DISTRIBUTORS, INC., DEUTSCHE ASSET & WEALTH MANAGEMENT

Kevin Rusli, Lawyer, BLAKE, CASSELS & GRAYDON LLP


PFEIFER
GRAND | HYATT
NEW YORK


NANOF


ABNER
KITTSLEY


PFEIFER

6:00 PM Opening Cocktail Reception







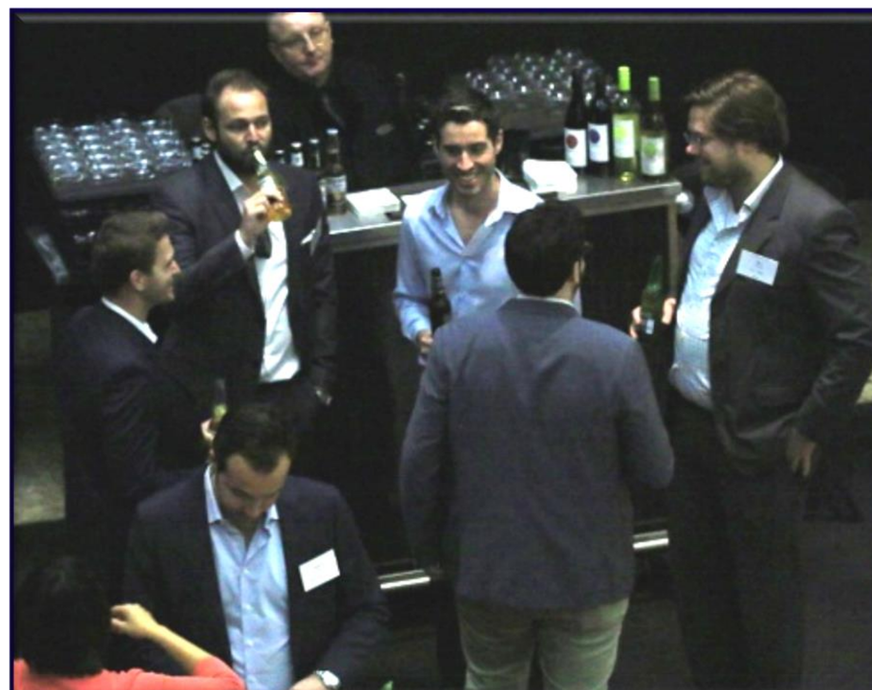



Mike









7:00 PM 12th Annual Global ETF Awards® Dinner

Guest appearance by Robert J. Shiller, Sterling Professor of Economics Yale University and winner of the Nobel Prize





2


6


3


11

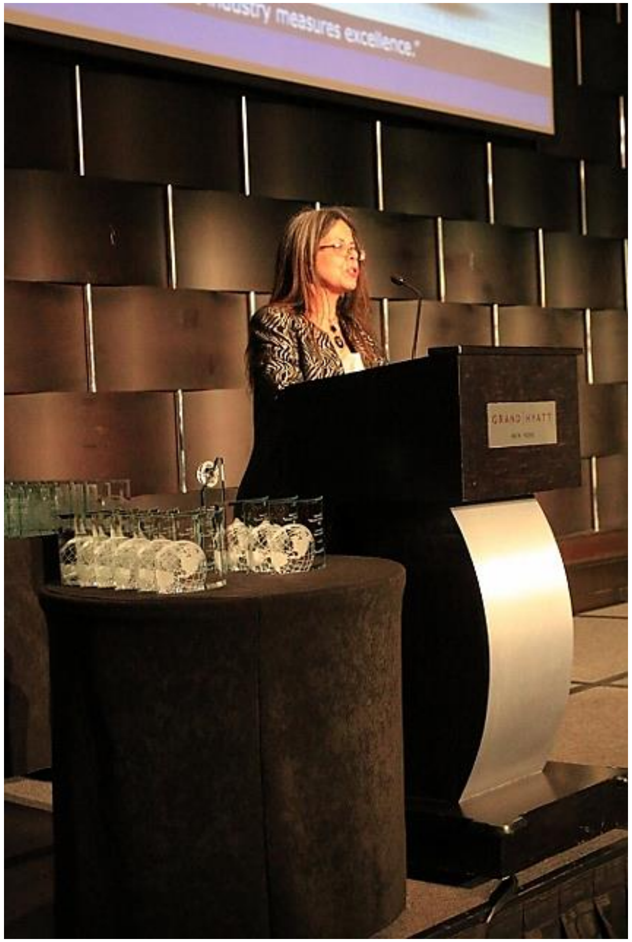

4


11


10

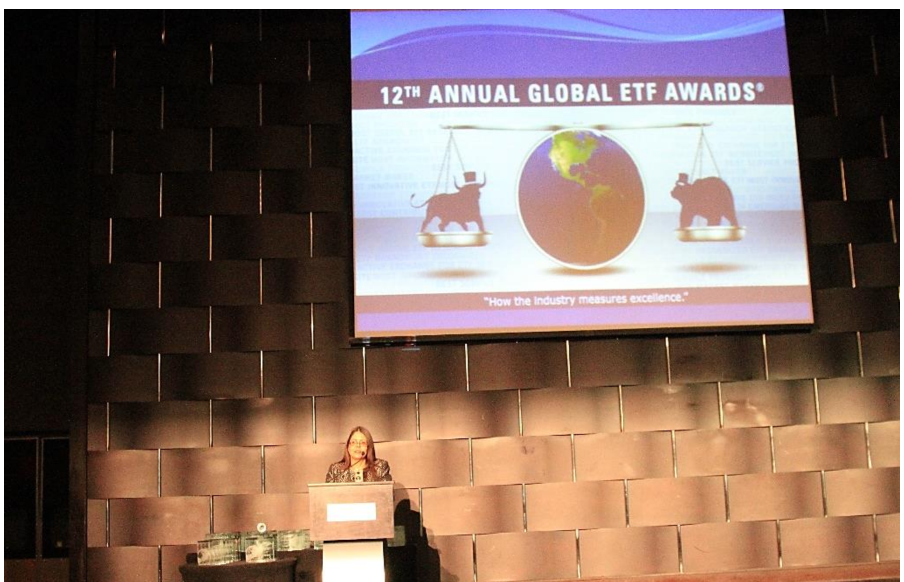

8


3


measures excellence."
GRAND HYATT


GRAND HYATT
NEW YORK


GRAND | HYATT
NEW YORK


12TH ANNUAL GLOBAL ETF AWARDS®
"How the industry measures excellence."


12TH ANNUAL GLOBAL ETF AWARDS®
"How the industry measures excellence."





GRAND HYATT


GRAND HYATT


GRAND HYATT
NEW YORK

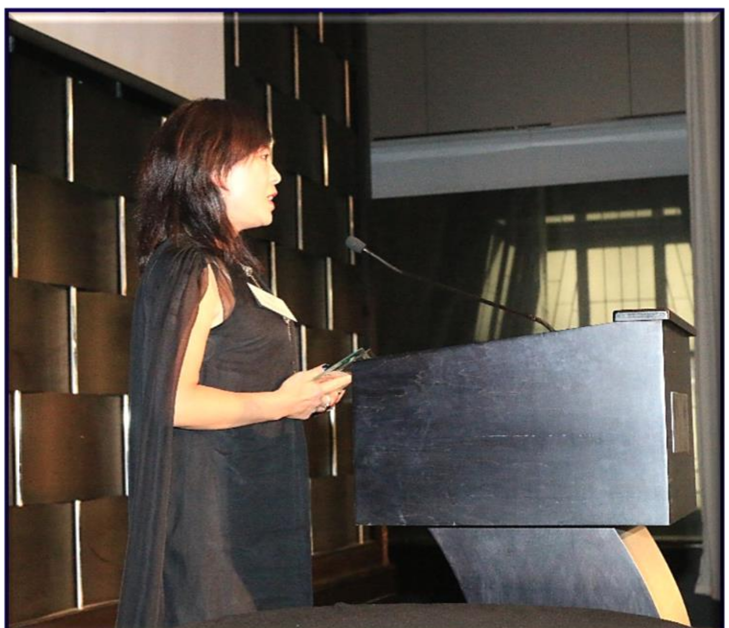

NYSE

























Nate Most Award
Greatest Contributor to the
ETF Marketplace
2015
iShares
GLOBAL ETF AWARDS®
"How the industry measures excellence"


BEST SERVICE PROVIDER
AMERICAS
2015
BNY MELLON
GLOBAL ETF AWARDS®
"How the industry measures excellence"


BEST SERVICE PROVIDER
EUROPE
2015
State Street Fund Services
(Ireland) Limited
GLOBAL ETF AWARDS®
"How the industry measures excellence"


ETF STRATEGIST
BEST GLOBAL INSIGHT
2015
WINDHAVEN
INVESTMENT MANAGEMENT
GLOBAL ETF AWARDS®
"How the industry measures excellence"

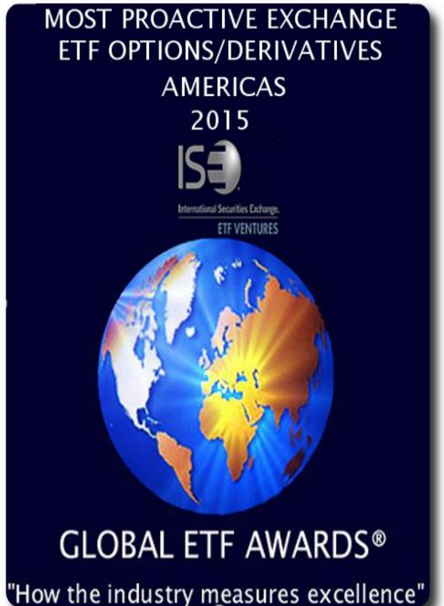

MOST INNOVATIVE ETF
EUROPE
2015
db x-trackers II Harvest CSI China
Sovereign Bond UCITS ETF
GLOBAL ETF AWARDS®
"How the industry measures excellence"

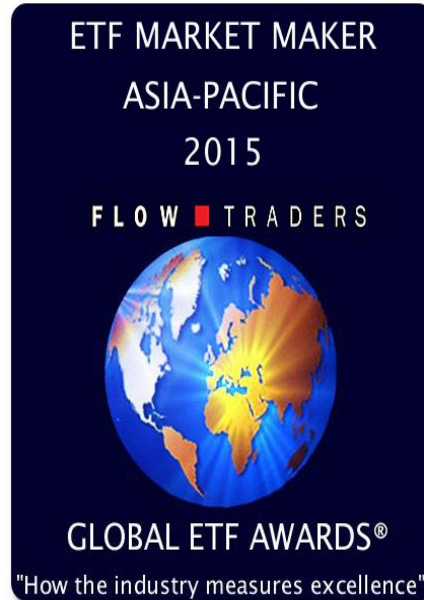

MOST INNOVATIVE ETF
AMERICAS
2015
The Reality Shares DIVS ETF
GLOBAL ETF AWARDS®
"How the industry measures excellence"

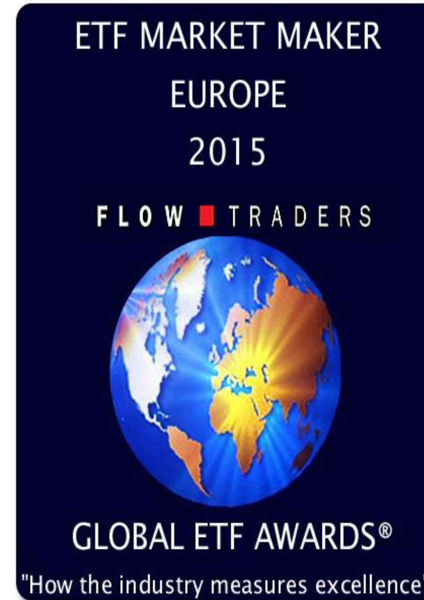

MOST INNOVATIVE ETF
EUROPE
2015
Ossiam Shiller Barclays Cape
Europe Sector Value
TR-UCITS ETF
GLOBAL ETF AWARDS®
"How the industry measures excellence"


MOST INNOVATIVE ETF
INDEX PROVIDER
EUROPE
2015
STOXX
GLOBAL ETF AWARDS®
"How the industry measures excellence"


MOST RECOGNIZED
ETF BRAND
Americas
2015
SPDR
GLOBAL ETF AWARDS®
"How the industry measures excellence"


MOST PROACTIVE EXCHANGE
ETF OPTIONS/DERIVATIVES
AMERICAS
2015
ISE
International Securities Exchange.
ETF VENTURES
GLOBAL ETF AWARDS®
"How the industry measures excellence"


ETF MARKET MAKER
ASIA-PACIFIC
2015
FLOW TRADERS
GLOBAL ETF AWARDS®
"How the industry measures excellence"


ETF MARKET MAKER
EUROPE
2015
FLOW TRADERS
GLOBAL ETF AWARDS®
"How the industry measures excellence"


MOST RECOGNIZED
ETF BRAND
ASIA-PACIFIC
2015
ChinaAMC
GLOBAL ETF AWARDS®
"How the industry measures excellence"


ETF MARKET MAKER
AMERICAS
2015
JANE STREET
GLOBAL ETF AWARDS®
"How the industry measures excellence"


MOST RECOGNIZED
ETF BRAND
EUROPE
2015
Lyxor
GLOBAL ETF AWARDS®
"How the industry measures excellence"


MOST USEFUL ETF RESEARCH
ANALYTICAL
EUROPE
2015
ETFGI
GLOBAL ETF AWARDS®
"How the industry measures excellence"

Thank you for joining us in celebrating 12 years of Industry Achievement®.

The 2016 Global ETF Awards® Dinner provides an opportunity for industry professionals worldwide to be recognized for their contributions to the growth of the ETF marketplace.

With the collaboration of various entities in the ETF, ETC and ETN marketplace, we were able to reach out to the global marketplace. Additionally, a series of awards were determined by analysis of statistical data were gathered from various sources, among them Deutsche Bank and XTF Inc.

We thank all the organizations that participated in the awards voting process for their effort and all event sponsors for their continued and generous support. We also extend a special thank you to the various contributors of the statistical data.

A complete list of winners and runner-ups can be found at: www.globaletfawards.com

The images that are embedded in this document are image thumbnails and have low quality resolution to allow for faster loading.
If you are interested in receiving copies of the photos (better resolution) or logos, please send an email to acr@globaletfawards.

Exchangetradedfunds.com

exchangetradedfunds.com

The Fundamental Law of Mismanagement[1]

By
Richard O. Michaud, Robert O. Michaud, and David N. Esch[2]

Draft: April 2016

[1] An earlier version with the same title by Richard Michaud and Robert Michaud was published as a New Frontier Advisors' Newsletter, July 2005.

[2] Richard O. Michaud is CEO of New Frontier Advisors, LLC, Boston, MA 02110. Robert O. Michaud is CIO of New Frontier Advisors, LLC. David N. Esch is Managing Director of Research, New Frontier Advisors, LLC.

Abstract
Active managers often claim superior risk-adjusted performance because they invest in many securities, use many factors to forecast return, trade frequently and optimize without constraints. Many long-short, hedge, and unconstrained strategies are based on these four principles of portfolio design. Such claims are due to applications of Grinold's (1989) "Fundamental Law of Active Management," by Grinold and Kahn (1995, 1999) and Clarke, deSilva, and Thorley (2002, 2006). In particular, Grinold and Kahn state: "It takes a modest amount of skill to win (the investment game) as long as that skill is deployed frequently and across a large number of stocks." We show that the Grinold formula treats asset management as a casino game that ignores estimation error and the role of constraints essential for properly defining portfolio optimality in practice.[*] We show with simple examples why the four principles fail followed by a rigorous simulation proof to confirm that all four fund fundamental law characteristics are essentially invalid and self-defeating. These flawed principles have been taught in academic and professional journals and promoted in conferences for twenty years and likely adversely impact many hundreds of billions of dollars or more in contemporary investment practice.

[*] Michaud, R., R. Michaud, D. Esch, 2015. "The Fundamental Law of Mismanagement." New Frontier Research. https://newfrontieradvisors.com/Research/Articles/documents/fundamental%20law%20A1%206-15-15.pdf and on www.ssrn.com and www.researchgate.com

The Grinold (1989) "Fundamental Law of Active Management," is one of the most widely referenced publications in contemporary investment theory and practice. The Grinold in-sample mathematical formula is based on unconstrained mean-variance (MV) efficient frontier optimization translated to the residual or benchmark relative return framework. Grinold asserts that the value added by an optimized MV investment strategy is proportional to the in-sample information ratio (IR), alpha over residual risk. He further decomposes the IR into the approximate product of two simple attributes of an investment strategy – square root of breadth (BR) and skill (IC).[3] The IC represents the manager's "information coefficient" or correlation of forecast and ex post return. Breadth represents the number of independent bets or factors associated with the strategy.

Based on the formula Grinold and Kahn (1995, 1999) (GK) state that: "The message is clear: you must play often and play well to win at the investment game. It takes only a modest amount of skill to win as long as that skill is deployed frequently and across a large number of stocks."[4] Their recommendations include increasing trading frequency, size of the optimization universe, and factors to models for forecasting return. There are three main assumptions that underlie their result: 1) accurate measure of IC; 2) independent sources of information, i. e. an information-rich universe that can always be mined for new independent sources of knowledge about investable securities; 3) IC the same for each component, i. e. maintainable over increases in breadth. GK use a roulette game framework to provide intuition for their results. Their principles are often used to rationalize many optimized portfolio investment strategies in current practice.

Clarke, de Silva and Thorley (2002, 2006) (CST) generalize the Grinold formula by introducing the "transfer coefficient" (TC). The TC is a scaling factor that measures how information in individual securities is transferred into managed portfolios given Grinold formula assumptions. In this in-sample framework, TC measures the presumed reduction in investment value from imposing optimization constraints. This widely influential article has been used to promote many variations of long-short and hedge fund equity investment strategies.[5]

A significant literature exists on applying the Grinold law and variations for rationalizing various active equity management strategies, particularly those associated with long-short and hedge fund portfolios. Extensions include: Buckle (2004), Qian and Hua (2004), Zhou (2008), Gorman et al (2010), Ding (2010), Huiz and Derwall (2011). Industry tutorials and perspectives include Kahn (1997), Kroll et al (2005), Utermann (2013), Darnell and Ferguson (2014). Teachings include the Chartered Financial Analyst (CFA) Institute Level 2, the Chartered Alternative Investment Analyst (CAIA) Level 1 and many conferences and graduate level courses in finance. Texts discussing the formula and applications include Focardi and Fabozzi (2004), Jacobs and Levy (2008), Diderich (2009), Anson et al (2012), Schulmerich et al (2015).

[3] Note that the Grinold optimization framework which is analytically derived is not to be confused with Markowitz (1952, 1959) which assumes linear (inequality and equality) constrained portfolios and requires quadratic programming techniques to compute the MV efficient frontier. In particular, the Markowitz efficient frontier is generally a concave curve even in a residual return framework while in Grinold (see e.g., GK 1995, p. 94) it is a straight line emanating from a zero residual risk and return benchmark portfolio.

[4] GK (1995, Ch. 6, p. 130), also GK (1999, Ch. 6, p. 162).

[5] One example is Kroll et al (2005). Michaud (1993) was the first to note possible limitations of the long-short active equity optimization framework.

The essential wisdom of the Grinold formula – adding an independent investment significant positive source of information adds investment value – is uncontroversial. However, investment intuition supported by rigorous simulation studies demonstrate that the Grinold based GK and CST principles are invalid in practice and often defeat the effective use of investment information, even if the three demanding assumptions above are satisfied. The errors are due to ignoring estimation error in risk-return estimates and inequality constraints required for properly defining out-of-sample portfolio optimality.[6] Markowitz (1952, 1959) MV optimization, other portfolio construction procedures, and much financial theory are similarly afflicted.[7] The GK and CST principles have been taught for many years and likely adversely impact many hundreds of billions of dollars or more in contemporary asset management.

The outline of the paper is as follows. Section 1 presents the Grinold formula, the GK and CST prescriptions for active management and a critique of their casino management rationale. Section 2 discusses the four fallacies associated with GK and CST prescriptions in investment intuitive terms. Section 3 presents a framework for our simulation studies addressing the Roll (1992) critique of benchmark optimization used in Grinold. Section 4 presents the Monte Carlo simulation studies that confirm and refine our conclusion that the principles commonly associated with the fundamental law are invalid and often self-defeating. Section 5 provides resolutions for practical active optimization under estimation uncertainty. Section 6 provides a summary and conclusions.

1.0 Grinold's Fundamental Law of Active Management

Grinold (1989) demonstrates that the in-sample value added of a MV inequality unconstrained optimized residual return investment strategy relative to an index or benchmark is proportional to the information ratio (IR) (alpha over residual risk). In Grinold's "Law of Active Management" the IR of a MV optimized investment strategy is shown to be (approximately) the product of the square root of the breadth (BR) and the assumed information correlation (IC).[8] Mathematically,

$$IR \cong IC * \sqrt{BR}$$

where IR = information ratio = (alpha) / (residual or active risk)
IC = information correlation (ex ante, ex post return correlation)
BR = breadth or number of independent sources of information.

The essential wisdom of the formula, that successful asset management depends on both the information level of the forecasts and the breadth associated with the estimates, is not in doubt. What is in doubt are the principles associated with the formula that the value of an optimized investment strategy necessarily increases with increasing numbers of assets in the optimization universe, number of factors in a multiple valuation framework and increased trading frequency in practical applications.

Clarke et al (2002) define the transfer coefficient (TC) as the cross-sectional correlation of risk-adjusted active weights with risk-adjusted forecasted residual returns for the securities in the

---

[6] The GK (1999 2nd ed.) discussion of uncertainty in IC estimation is independent of estimation error uncertainty in portfolio optimality, the subject of this paper. Esch (2015) further discusses IC estimation issues.
[7] For further discussion see Michaud (1989, 1998), Michaud and Michaud (2008a, 2008b) and Section 5.2 below.
[8] The derivation is given in GK, Ch. 6, and Technical Appendix.

optimization universe. With additional assumptions they show that the TC can be incorporated into the Grinold formula and acts as a multiplicative scaling (a number between 0 and 1) of the IC. As constraints are added to the optimization, the TC is shown to diminish from its theoretical optimal value of one. From this point of view constraints limit the value of the information in the strategy and rationalize various long-short and unconstrained hedge fund strategies.

There are two fundamental reasons for limitations of principles derived from the Grinold law for practical asset management: 1) the formula ignores the impact of estimation error in investment information on out-of-sample investment performance; 2) the formula assumes an unconstrained MV optimization framework and ignores the necessity of including many economically meaningful inequality constraints required for defining portfolio optimality in practice. We show that GK and CST prescriptions associated with the formula are not reliable and generally not recommendable for practice.

1.1 The Casino Game Rationale

GK provide a revealing rationalization of the implications and applications of their formula with reference to casino roulette games. In a casino the return distribution and hence the IC of plays of the roulette wheel is known, positive, and stable, and separate spins of the wheel are independent. In this case the Grinold formula under the assumptions gives the (nearly) correct economic value of the plays of the casino game. In contrast, the IC of the plays of an investment game has estimation error, may be insignificantly or even negatively related to return, is likely to be unstable, and multiple plays may not be independent. The IC will also depend on changes in the frequency of investing and size of the universe. Increasing the number of plays of an investment game if the return distribution or IC is unreliably positive may often be undesirable. Moreover, even with a stable true IC, the Grinold formula breaks down in the presence of estimation error as breadth is increased, and the CST prescription to remove constraints may negatively impact portfolio value under estimation error.

Investing is not a casino game and asset managers do not know with certainty the risk and return distribution ex ante in practice.[9] The following sections explore the implications of estimation error and inequality constraints on the GK and CST proposals for asset management.

2.0 Discussion of GK and CST Prescriptions

The four principles for investment strategy that are associated with GK and CST are: 1) increasing size of the optimization universe; 2) invest often or frequent trading; 3) add factors to forecast model; 4) remove constraints. In this section we discuss the limitations of each prescription from an intuitive point of view.

2.1 Large Optimization Universe Fallacy

GK argue that investment value increases with the size of the optimization universe on the condition that that the IC is roughly equal for all securities in a given optimization universe. How realistic is this assumption?

[9] The use of insider information is illegal under U.S. security laws.

For a small universe of securities the assumption of uniform average IC may be tenable. Small universes may be fairly homogeneous in character. However, for a large and expanding optimization universe, it seems evidently untenable to assume uniform average IC across all subsets. Any manager will naturally use the securities with the best information first. While theoretically, adding more assets may add marginally to breadth, all other things the same, it is also likely to result in less predictable securities and reducing the overall average IC level of the universe. A lower level of average IC is undesirable according to the formula and may cancel any gains made by increasing breadth by increasing size.

The issue can be framed in a more common practical setting. Consider an analyst suddenly asked to cover twice as many stocks. Given limitations of time and resources, it is highly unlikely that the analyst's average IC is the same for the expanded set of stocks. Issues of resources and time rationalize why analysts tend to specialize in areas of the market or managers in investment strategies that limit the number of securities that they cover. In practice many traditional managers limit the number of securities they include in their active portfolio to not much more than twenty or fifty. Except for relatively small asset universes, the average IC and overall level of IR may often be a decreasing function of the number of stocks in the optimization universe, all other things the same. Grinold and Kahn seem to be aware of these limitations, for example as suggested by their statement "The fundamental law says that more breadth is better, provided the skill can be maintained." Nevertheless, this important caveat is omitted from their final summary and often ignored by practitioners who may not have accurate knowledge of their true IC, especially when coverage increases to larger universes of assets and/or factors.

2.2 Multiple Factor Model Fallacy

Large stock universe optimizations often use indices such as the S&P500, Russell 1000 or even a global stock index as benchmarks. In this case individual analysis of each stock is generally infeasible and analysts typically rely on factor valuation frameworks for forecasting alpha. For example, stock rankings or valuations may be based in part on an earnings yield factor.[10] As GK note, if earnings yield is the only factor for ranking stocks, there is only one independent source of information and the breadth equals one.

In the Grinold formula, the number and quality of factors used to forecast alpha are positively related to one or both of BR and IC. The formula shows that the IR increases with the number of independent positive significant factors in the multiple valuation forecast model. However, in practice, asset valuation factors are often highly correlated and may often be statistically insignificant providing dubious out-of-sample forecast value.[11] Finding factors that are reasonably uncorrelated and significantly positive relative to ex post return is no simple task.

Factors are often chosen from a small number of categories considered to be relatively uncorrelated and positively related to return such as value, momentum, quality, dividends, and discounted cash flow.[12] In experience, breadth of multiple valuation models is typically very limited

---

[10] Some standard methods for converting rankings to a ratio scale to input to a portfolio optimizer include Farrell (1983) and references. Michaud (1998, Ch. 12) notes some common scaling errors.

[11] There is a limit to the number of independent investment significant factors even in many commercial risk models, often far less than ten.

[12] Standard methods such as principal component analysis for finding orthogonal risk factors are seldom also reliably related to return.

and unlikely to be very much greater than five independent of the size of the optimization universe.[13,14] As in adding stocks to an optimization universe, adding factors at some point is likely to include increasingly unreliable factors that are likely to reduce, not increase, the average IC of an investment strategy.

Michaud (1990) provides a simple illustration of adding factors to a multiple valuation model. While adding investment significant factors related to return can be additive to IC, it can also be detrimental in practice. There is no free lunch. Adding factors can as easily reduce as well as enhance forecast value, and the number of factors that can be added while maintaining a desirable total IC is severely limited in practice.

2.3 Invest Often Fallacy

GK recommend increasing trading period frequency or "plays" of the investment game to increase the BR, and thus the IR of a MV optimized portfolio. The Grinold formula assumes trading decision period independence and constant IC level. However, almost all investment strategies have natural limits on trading frequency.[15] For example, an asset manager trading on book or earnings to price will have significant limitations increasing trading frequency smaller than a month or quarter. Reducing the trading period below some limit will generally reduce effectiveness while increasing trading costs.

Fundamentally, trading frequency is limited by constraints on the investment process relative to investment style.[16] Deep value managers may often be reluctant to trade much more than once a year while growth stock managers may want to trade multiple times in a given year. Increased trading, to be effective, requires increasing the independence of the trading decision while maintaining the same level of skill. This will generally require increased resources, if feasible, all other things the same. The normal trading decision period should be sufficiently frequent, but not more so, in order to extract relatively independent reliable information for a given investment strategy and market conditions.

It is worth noting that the notion of normal trading period for an investment strategy does not imply strict calendar trading. Portfolio drift and market volatility relative to new optimal may require trading earlier or later than an investment strategy "normal" period. In addition a manager may need to consider trading whenever new information is available or client objectives have changed. Portfolio monitoring relative to a normal trading period including estimation error is further discussed in Michaud et al (2012).

---

[13] See e.g., Michaud (1999).

[14] While principal component or factor analysis procedures for identifying orthogonal factors in a data set may be used, most studies find no more than five to ten investment significant identifiable factors that are also useful for investment practice.

[15] Special cases may include proprietary trading desk strategies where the information level is maintained at a reasonable level and trading costs are nearly non-existent. Other cases, such as high frequency and algorithmic trading are arguably not investment strategies but very low level IC trading pattern recognition relative to highly sophisticated automated liquidity exchange intermediation.

[16] Trading costs and market volatility are additional considerations.

2.4 Remove Constraints Fallacy

Markowitz's (1952 1959) MV optimization can accommodate linear equality and inequality constraints. In actual investment practice, MV optimized portfolios typically include many linear constraints. This is because unconstrained MV optimized portfolios are often investment unintuitive and impractical. Constraints are often imposed to manage instability, ambiguity, poor diversification characteristics, and limit poor out-of-sample performance.[17] However, constraints added solely for marketing or cosmetic purposes may result in little, if any, investment value and may obstruct the deployment of useful information in risk-return estimates.

In general, inequality constraints are necessary for defining portfolio optimality in practice. Inequality constraints reflect the financial fact that even the largest financial institutions have economic shorting and leveraging limitations. Recently, Markowitz (2005) demonstrates the importance of practical linear inequality constraints in defining portfolio optimality for theoretical finance and the validity of many tools of practical investment management. Long-only constraints limit liability risk, a largely unmeasured factor in most portfolio risk models and often an institutional requirement. Regulatory considerations may often mandate the use of no-shorting inequality constraints. Performance benchmarks may often mandate index related sets of constraints for controlling and monitoring investment objectives.

In an important early study, Frost and Savarino (1988) demonstrate that sign or non-negative inequality constraints may limit the impact of estimation error and consequently improve out-of-sample investment performance, contradicting CST. This is because economically valid constraints act like Bayesian priors focused on portfolio structure rather than the return estimation by enforcing rules representing legitimate information not contained in the optimization. Such restriction can mitigate estimation error in risk-return estimates implicitly by forcing the solutions towards more likely optimal portfolios.

3.0 Residual and Total Return MV Optimization

The Grinold MV active management framework reflects much investment practice. An active manager is typically hired to explicitly beat some benchmark such as the S&P 500 or Russell 1000 index while limiting tracking error or residual risk. The mathematical consequence of using a residual rather than total return framework is simply a revision of the MV optimization budget constraint to sum to zero instead of one relative to index weights, and a consequent reformulation of the variance component of the utility objective. Interestingly, contemporary commercial equity risk models are often defined for either total or residual return optimization. The notion is that the optimal MV residual return portfolio for a specified index tracking error can also be estimated as a total return MV optimization calibrated to the desired tracking error. However, any practical benefits associated with the residual return MV optimization framework may often be associated with serious investment limitations.

3.1 The Roll Critique

Roll (1992) provides a serious critique of the Grinold active return MV optimization framework. Roll shows that if the index is not total return MV efficient all the portfolios on the index relative efficient frontier are dominated in total return MV space. This means that there are always

[17] Jobson and Korkie (1980, 1981), Michaud (1989).

portfolios with less risk or more estimated return or both than any portfolio on the residual return efficient frontier. The presumed convenience of optimizing a portfolio relative to a given benchmark can lead to very poor investments. On the other hand, as Roll notes, if the index is MV efficient, the total and residual return efficient frontiers coincide and the residual return optimized portfolios are also total return MV efficient. In this case portfolios on the MV total return efficient frontier are also residual return MV efficient relative to some level of tracking error and maximization of IR is equivalent to max Sharpe ratio (MSR) optimization in total return space.

From the point of view of rational markets, it is hard to justify the IR optimization framework if the index is not, in some investment meaningful sense, at least approximately MV efficient.[18] We note that a framework where the Grinold assumptions are also valid for total return MV optimization is a best case for understanding the practical investment limitations of the GK and CST prescriptions. It is also important to avoid the Roll critique as an explanation for poor performance in our simulation experiment, which is designed to rigorously demonstrate the limitations of GK and CST principles in the context of estimation error.

3.2 Merton (1987) and Benchmark MV Efficiency

In an important paper for investment practice, Merton (1987) proposes an information cost structure model of MV market equilibrium. In his study he presents relatively simple conditions under which common benchmarks in active management practice may be considered essentially total return MV efficient.

Merton's incomplete information framework posits constraints and information levels where investors act as if they do not know many firms in large capital markets.[19] In this case, the cost of information limits the market portfolio that can be efficiently considered for investment. For example, a small cap stock manager may claim specialized expertise for managing a benchmark of small cap stocks relative to a larger universe of securities but little if any for large cap. Institutional investors often consider it optimal to hire managers with specialized expertise in different segments of the market, hoping that the total will exhibit a globally enhanced level of return for given risk level.

In the Merton model, expected return reflects a discount factor for the subset of information available stocks. As Merton notes, there are many possible frameworks for justifying the notion of market equilibrium in incomplete information. These may include prudent-investing laws, regulatory constraints, and short-sale proscriptions.

Merton's framework rationalizes a variety of contexts that are consistent with actual sophisticated asset management. In the incomplete information case and in variations, the benchmark can be assumed essentially total return MV efficient. Alternatively, the contrapositive of the generalized Merton framework implies the existence of managers willfully managing money inefficiently and sophisticated investors and institutions willingly investing in such strategies, a contradiction of

[18] One rationale noted by Roll is that estimation error is so extensive that the benchmark may not be statistically indistinguishable from MV efficiency.

[19] Note that a benchmark consistent with the Merton incomplete information framework requires economic considerations and is inconsistent with actuarial based liability driven investing (LDI) popular with many actuarial and some pension consulting firms. See Michaud (1998, Ch. 10) and associated references for defining a liability benchmark based on economic principles.

rational markets. As Roll notes, the notion of an index that is not, in some fundamentally meaningful sense, MV efficient raises important investment issues independent of those in this report.

Our working assumption in our experimental design is that the benchmark can be assumed MV efficient relative to some set of constraints and assumptions including information costs. In this case the IR characteristics of the unconstrained MV optimal portfolio in a residual return framework can be equivalently analyzed with respect to the properties of maximum Sharpe ratio optimal portfolios in total return MV space. We will often refer to maximizing IR and MSR interchangeably, and we conduct the experiment itself in total return space to avoid doubt about how to plausibly simulate a benchmark.

4.0 GK and CST Simulation Proofs

While section 2 provides a number of challenges to many of the notions of GK and CST for practice, the narrative is largely based on investment intuition and practice rather than rigorous demonstration. In this section we address the limitations of the GK and CDT for practice within a rigorous simulation framework.[20]

4.1 Jobson and Korkie Simulation Studies

The Grinold MV framework assumes estimation error free unconstrained MV optimization. Jobson and Korkie (1981) (JK) provide the classic study of the effect of estimation error on the out-of-sample investment value of inequality unconstrained MV optimized portfolios. By means of a simulation study designed much like the one in this paper, they show that the additional performance gain from an unconstrained MSR optimization is more than cancelled out by the loss incurred by a realistic level of estimation error, i. e. that equal weighting substantially outperforms unconstrained Sharpe ratio maximization under a realistic amount of estimation uncertainty. Their study is performed with total-return optimization rather than benchmark-relative active-weight optimization, but their result can be extended to active weight optimization since the optimal frontiers are identical if the benchmark is efficient, and if not, the performance of the active-weight optimization can only be worse since the active-weight frontier is mathematically dominated everywhere by the total-return optimal one.[21]

In contrast to JK study's use of estimation periods as a proxy for the degree of estimation error and thus the information level of the analysis in their experiment, GK use average IC and not estimation periods to represent information level in practice. For example, an equity portfolio manager may claim an average 0.10 IC to reflect their anticipated correlation between forecasts and ex post returns for a given investment strategy. However, the two concepts are closely related; i.e., increasing estimation periods increases the IC of the simulated forecasting process.[22] It is important to note that the average IC associated with a given number of estimation periods also depends on the risk-return distribution of the case-specific optimization universe. While estimation periods

---

[20] Note that simulation proofs used in many recent studies are superior to any back tests of investment effectiveness. A back test is always time period dependent and unreliable out-of-sample.

[21] Michaud (1998, Ch. 4) replicate the JK simulation studies based on a data set of six diversified country equity and two bond indices and found qualitatively similar results considering the different character of the historical risk-return distribution.

[22] The 60 estimation periods in the JK study represents roughly an IC of 0.45.

may be a more reliable engine to drive estimation error in a Monte Carlo simulation process, we will use the Grinold framework IC to define ex ante information level in our simulations.[23]

4.2 Simulating Breadth while Maintaining Information Levels

One of the fundamental GK precepts is the notion that simply adding securities as a way of adding breadth (BR) leads to improved MV optimized out-of-sample investment performance all other things the same. In the following we generalize the JK simulation framework to illustrate the impact of estimation error on out-of-sample investment value relative to optimization universe size, while maintaining a constant IC across all universe sizes. Although the case has been made that there are practical limits in the real world for increasing breadth while maintaining IC, we do not wish any failure in performance as breadth increases in our experiment to be attributable to a loss in IC.

Although the number of assets is not identical to breadth as specified by GK and CST, the particular construction of the simulated covariance matrix that we are using guarantees that we are adding breadth as we continue to add assets to the case, since each asset is given some idiosyncratic variance in the model, and the covariance is guaranteed to have full rank.[24] Basing an estimation process on data from a greater number of assets in this simulation framework provides new independent information since each asset has a residual variance that is partly explained by the increased cardinality of the estimation. It is never true that we are using the best assets that explain the most of the total variance of all the assets first, as would likely be the case in a real investment situation. We are still adding breadth up to the last increment in portfolio size, and the results cannot be explained as breadth leveling off as a function of portfolio cardinality.

4.3 Simulation Methodology

We calculate a truth for the purposes of simulation based on monthly data taken from the Russell 1000 index.[25] Using real return estimates for our simulation parameters provides good coverage of the return distribution from a recent history (2012-2013) of this index, while our methodology guarantees a limitless supply of simulated breadth at a constant IC.[26]

An important factor that can greatly reduce the average IR of an optimized portfolio is ill-conditioning of the covariance matrix. When the covariance matrix is calculated using the sample covariance of historical data, this performance-killing effect creeps in as the number of assets

[23] Simulations were designed to attain a particular level of average IC by combining the target mean with some independently sampled noise. More information is available in Esch (2015)..

[24] A number of earlier versions of the Grinold law misidentified the N in breadth as the number of stocks.

[25] We include all listed U. S. stocks in the CRSP database that had two years of continuous monthly returns from January 2012 to 2013. We excluded returns greater than 50% or less than -50%. We found 5307 stocks that met our criteria.

[26] Choosing only securities with a fixed minimum available history creates survivorship bias and paints an overly positive portrait of expected return. In order to compromise between this selection bias and a realistic return distribution including returns from the low end of the spectrum, we have limited the historical data requirement to two years. This selection criterion still errs on the side of optimism, since real-world baskets of selected stocks are likely to produce returns biased negatively relative to the predictions of the experiment. Although using only two years of history definitely introduces estimation error, in aggregate the set of estimates, with estimation error, should provide good coverage of the true return distribution of real stock returns of investable stocks. We also performed simulation experiments with other datasets with different history requirements, and reached exactly the same conclusions Although using only two years of history definitely introduces estimation error, in aggregate the set of estimates, with estimation error, should provide good coverage of the true return distribution of real stock returns of investable stocks. These supplemental experiments are not shown here due to space limitations.

approaches the number of time periods in the estimation process. In practice, the covariance matrix for an equity optimization is likely to be obtained as the output of a factor model complete with an idiosyncratic variance term for each asset. By construction these estimates for the covariance matrix will always be full rank and reasonably well-conditioned, and performance as measured by IR will not suffer because of ill-conditioning. In our experiment we do not wish to test the impact of near-singularity of the covariance matrix, so we simulate the variance parameters (not the estimates) of the entire sampling pool of assets in such a way that well-conditioning is guaranteed for portfolio sizes up to 500 in our examples. This is almost certainly optimistic with respect to practice, so our findings on the out-of-sample performance of the fundamental law's predictions represent a best-case scenario, and real world applications are likely to fare worse.

We use the direct estimates from the real two year histories to represent truth in the simulation experiment. From this "true" return distribution we simulate estimates which would correspond to the inputs in a practitioner's optimization. These estimates are designed to be consistent with their targets while including estimation error, all maintaining both a particular expected IC for the mean estimates[27] and a well-conditioned covariance estimate.[28]

Portfolios are then created from the simulated mean and variance input sets via three methods: unconstrained maximum Sharpe ratio, maximum Sharpe ratio with positivity constraints, and equal weighting. Of course numerous other methods are possible, but not presented here due to space limitations. Information ratios are then calculated for each method using the population values. These are not the in-sample information ratios that an investor would calculate using his or her own estimates; they are the true population information ratios which are calculable only within the experiment using the simulation parameters. Generally the in-sample estimates are far too optimistic, and indeed, although they are not shown on these graphs, their ranges dominate the others on the graph. For reference we also calculated the ranges of theoretical true maximum Sharpe ratios using the population parameters. Of course in practice these portfolios would be

---

[27] Details of simulating with a particular IC are given in Esch (2015). The nominal ICs shown in this experiment are likely inflated from their counterparts in the real world, since ICs are typically calculated as the correlations between estimates and realized returns, rather than true return expectations. As shown in Esch (2015) this has the effect of inflating the IC by the ratio of the total standard deviation of the realized returns divided by the standard deviation of the selected expected return due to the portfolio sampling process.

[28] Procedurally, we use the Ledoit (2003, 2004a, 2004b) covariance estimator on a short simulated history for the sampled subset within each simulation cluster, which creates a stable and full-rank estimate even when the dimensionality of the matrix exceeds the sample size. We use a small sample size of only ten observations here to create some error about the true covariance matrix. We feel that it is necessary to introduce some estimation error since the model assumption of a stationary covariance matrix is likely to be false, and in spite of their popularity and marketing claims, real-world factor models come with estimation error. In our experiments we found that larger sample sizes created estimates that were for practical purposes too close to their population values. After the "model" covariance is calculated as the Ledoit estimate of the dataset, repeated subsamples are drawn that are tightly clustered around these model covariances, by sampling from a Wishart distribution with degrees of freedom safely greater than the largest sample size in the experiment, in order that the matrices used in optimization will never suffer from ill-conditioning problems. This two-step simulated estimation process may seem unnecessarily complicated, but it successfully avoids the performance-killing ill-conditioning typical of matrices drawn from the thin information available for maintaining reasonably current estimates, and provides a good simulation of the estimation error implied by the paucity of relevant data to the current time period. Thus the step that provides the estimation error is the Ledoit step, taken with only ten time periods, and multiplicity is provided in the Wishart step, which is also done each time with a different set of assets, so the tight clustering of estimates provided by this method will not matter since each estimate is for a different asset mix.

unattainable since they represent flawless estimation when only imperfect information is obtainable in practice.

In the simulation studies that follow we differentiate two cases that reflect investment practice: asset allocation and equity portfolio optimization strategies. Asset allocation strategies typically include five to thirty securities and rarely more than fifty. On the other hand equity portfolio optimization strategies may include hundreds or even thousands of assets in the optimization universe. In both asset allocation and equity portfolio optimization we consider IC values of 0.10 and 0.50. While active equity asset managers may often claim to have an IC level of approximately 0.10 a more optimistic IC of 0.50 may be useful to bracket our results illustrating GK principles.

4.4 Russell 1000 MV Optimization Simulation Results

Figures 1 and 2 each consist of two panels of simulation results corresponding to IC levels of 0.10 and 0.50. Figures 1A and 1B display simulation results for universe sizes up to 50 stocks representing the asset allocation case. Figures 2A and 2B display simulation results for universe sizes up to 500 stocks and represent the equity portfolio optimization case. Four sets of ranges are displayed in each panel, each showing quantile ranges from 1,000 simulations of resampled data from the selected simulation universe. The dotted "theoretical max" series presents the averages and ranges of Sharpe ratios for in-sample inequality unconstrained MV optimized MSR portfolios. For this case the exact simulation parameters with no estimation error are used. Of course the Sharpe ratios in this result series are unattainable in practice since they use unavailable inputs. However, the other three graphed series show ranges of Sharpe ratios resulting from estimates based on available data, simulated with realistic and perhaps optimistic error. The "unconstrained" series displays the out-of-sample averages and ranges of Sharpe ratios of the simulated unconstrained MSR portfolios. The "equal weight" series displays the average Sharpe ratios of equal weighted portfolios. The "constrained" series reflects the average Sharpe ratios of out-of-sample simulated long-only MSR portfolios. Intervals are also shown in all cases, showing the central 90% of the simulated information ratios. In other words, the crossed lines mark the 5% and 95% quantiles of the simulated portfolio Sharpe ratios. The intervals as shown on the page are jittered horizontally so as not to overlap and to maintain readability of the chart.

The simulations demonstrate the interaction of constraints, optimization methods, sample size, and information coefficients. The "theoretical max" series assumes no estimation error in the optimization process. In this case the results are plausibly consistent with the GK view that adding assets increases the investment value of MV optimized portfolios proportionally to the square root of BR. The unattainability of this level of performance in practice is clearly demonstrated by the inferior performance of the feasible methods.

Note that our simulations assume that the average level of IC is constant independent of universe size, ignoring any realistic limitations on manager information. Consequently, a larger universe corresponds to a larger level of investment information, all other things the same. As a result, the slowly rising level of unconstrained average maximum Sharpe ratios as universe size increases is a necessary artifact of the simulation framework. In practice, adding assets is unlikely to add investment value beyond some optimal size universe consistent with the investor's level of information all other things the same. Indeed, beyond some optimal point, the unconstrained curve is likely to curve downward as the size of the optimization universe increases in applications. Our experiment is designed with deliberate optimism to distill the impact of estimation error on the fundamental law's predicted performance.

Figure 1A

Average Max Sharpe Ratios with IC 0.10

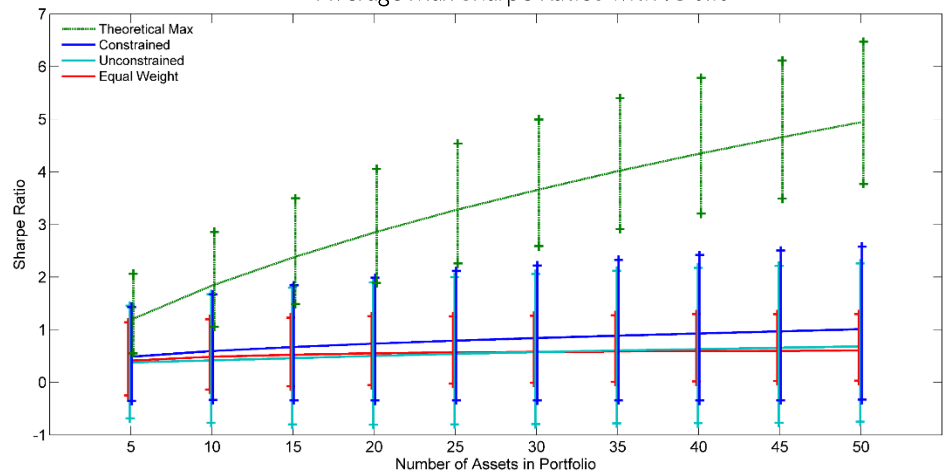


Figure 1B

Average Max Sharpe Ratios with IC 0.50

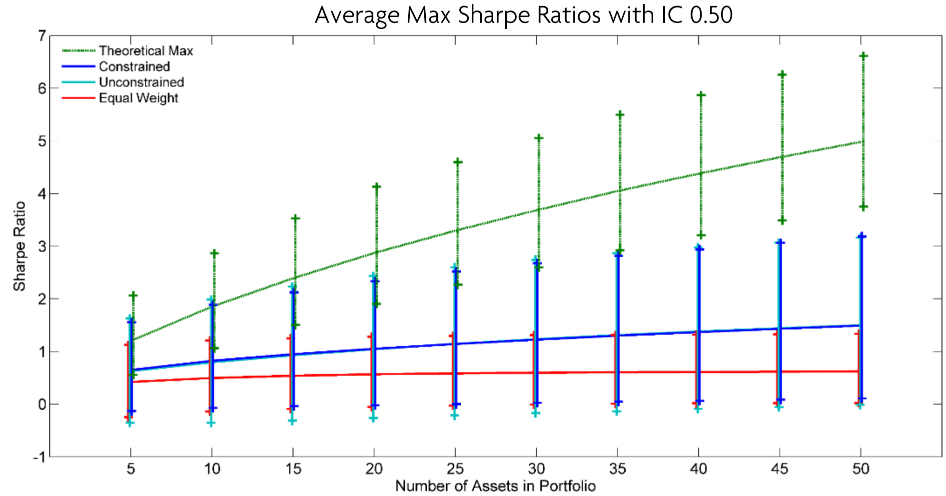


Figure 1: Maximum Sharpe Ratio ranges for three different portfolio construction methods and two different information coefficients for the asset allocation case, compared with corresponding ranges of MSRs of the unattainable perfect information frontiers. This experiment was run on many simulated resamplings of up to fifty U. S. stocks which had at least 2 years of contiguous monthly price data ending in December 2013.

The results of our experiments for the asset allocation cases demonstrate a definite failure of the GK and CST specifications of the fundamental law of management. In Figure 1A, the unconstrained portfolios dramatically underperform both sign constrained and equal weighting. While adding assets increases the Sharpe ratios of unconstrained portfolios out-of-sample, the gain is minimal and, we will argue below, unrealistic. How positivity constraints help the optimization process depends on the quality of information and universe size but the results generally contradict the

CST view that eliminating constraints adds investment value.[29] In all cases in Figure 1, positivity constraints narrow the confidence intervals. The naïve analyst may think *a priori* that performance will increase because of increased IR forecasts calculated with estimates used in the optimization, but such in-sample calculation amounts to assuming perfect information and estimation ability, clearly unrealistic for investors of any skill level. Our results vividly demonstrate the hazards of ignoring estimation error when optimizing.

Figure 2A

Average Max Sharpe Ratios with IC 0.10

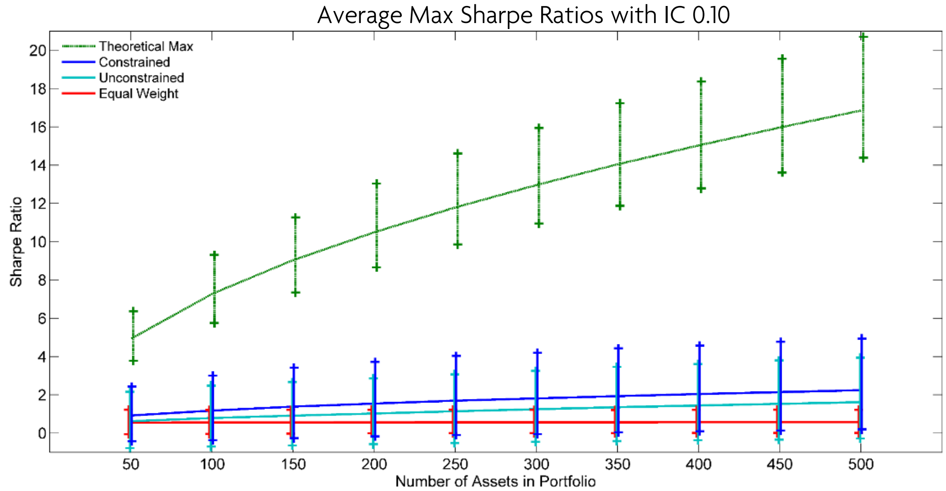


Figure 2B

Average Max Sharpe Ratios with IC 0.10, No Covariance Error

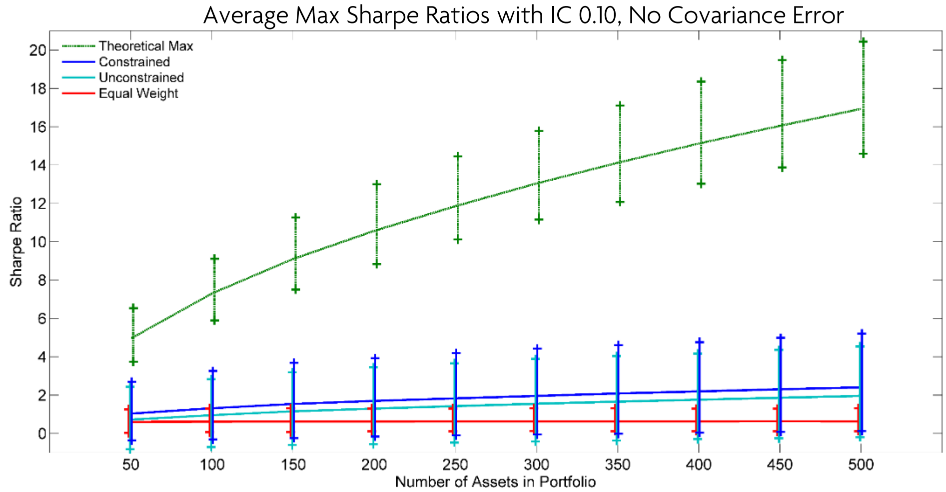


Figure 2: Maximum Sharpe Ratio ranges for three different portfolio construction methods and two different information coefficients for the equity portfolio case, compared with corresponding MSR ranges of the unattainable perfect information frontiers. This experiment was run on many resampled portfolios of up to five hundred U. S. stocks which had at least 2 years of contiguous monthly price data ending with December 2013.Figures 2A and 2B can be viewed as an extension of charts 1A and 1B to larger optimization universes.

Our deliberate optimism in setting up the simulation has important implications. The unconstrained cases would likely exhibit poorer IR performance in practice. Since almost all of the assets in the

[29] We note that the results reaffirm the conclusions in Frost and Savarino (1988).

simulation universe are likely to have some investment value, the investor is not harmed by putting portfolio weight on the "wrong" assets. In the real world, in which the investable universe is not limited to stocks which will have any particular track records, constraints limit the harm caused by misinformation. This effect was clearly demonstrated and measured in Jobson and Korkie (1981). In a truly chaotic world with a lot of estimation error and bias, the equal weighted portfolio, which uses no information to distinguish among assets, can be hard to beat.

Figure 2 presents similar simulation experiments to Figure 1 for expanded optimization universes of up to 500 securities. One clear difference in the large universe case is the overall inferiority of equal weighting particularly given the presence of significant levels of information. A second important difference is that the benefit of positivity constraints depends crucially on the level of presumed forecast information. For a typical level of IC = 0.10, sign constrained large universe optimization provides similar performance relative to unconstrained for much of the size spectrum. In the likely unattainable level of IC = 0.50 associated with large stock universe equity portfolio optimizations as in Figure 2B, unconstrained dominates. These results should not be surprising; nor do they represent any serious contradiction to our basic thesis that adding securities adds little if any investment value, all other things the same.

To summarize, our simulation experiment suggests several important conclusions. In real investment settings, an IC of 0.1 is optimistic, and most relevant to practice of the cases within our study. We offer the following guidelines based on our experiments: 1) Equal weighting beats unconstrained optimization for realistically attainable information levels and is far less risky overall. The underperformance of unconstrained optimization relative to equal weighting is substantial enough to warrant general avoidance of unconstrained MSR optimization. 2) Long-only constraints provide reliable performance gains over unconstrained optimization, and in most practical settings, over equal weighting as well. 3) Universe size does not matter beyond a point, usually much smaller than the overall universe, and probably smaller than much existing investment management practice. Increasing breadth past this saturation point, where the curves level off in the graphs, will provide no additional benefit, and only incur unnecessary costs.

5.0 Prescriptions and Caveats

Merton (1987) posits that the appropriate optimization universe should be defined only for securities with reliable information. Intuitively, managers should optimize only on what they know. Investing in large stock universes that include many low-information securities is likely to be suboptimal. But the Merton rule is an important limitation in a number of practical applications. In addition, estimation error uncertainty remains a key consideration for effective asset management.

5.1 The Composite Asset

Asset managers are often mandated to outperform an index while holding tracking error within a specified range. Defining the optimization universe solely for investment significant alpha securities may expose the optimized portfolio to unacceptable tracking error risk in the context of large stock universe benchmarks. Michaud and Michaud (2005) provide a reconciliation of these competing objectives. They recommend adding an index weighted "composite asset" to represent the non-investment significant alpha securities to the set of investment significant alpha securities as part of the optimization universe. Adding the composite asset does not violate Merton's theoretical prescription while satisfying the need for controlling tracking error risk in applications.

Michaud and Michaud find that an optimized portfolio that includes consideration of estimation error with a composite asset for non-investment significant assets often exhibits very desirable optimization and portfolio risk characteristics.

5.2 Optimization in Uncertainty

Michaud (1998) and Michaud and Michaud (2008a, 2008b) MV efficient frontier optimization is a generalization of the linear constrained Markowitz efficient frontier that includes estimation error in investment information in its portfolio construction methodology.[30] Monte Carlo sampling of risk-return estimates from their uncertainty distributions is used to address uncertainty in investment information by creating thousands of statistically similar Markowitz MV efficient frontiers. An averaging process over these many alternatives defines the new Michaud efficient frontier.[31,32] Simulation studies demonstrate that the resulting efficient frontier portfolios have superior investment value on average out-of-sample relative to Markowitz.[33] In this case neither GK nor CST provide added investment value all things the same. The investment game mandates investment significant investment information thoughtfully considered and properly utilized.

5.3 Resolutions

Merton advocates investing in only what you know. Michaud advocates understanding how much you know, then appropriately dealing with the remaining uncertainty in information when investing. Important considerations are often ignored by naïve interpretations of the fundamental law. GK is best understood as a theoretical framework for understanding the potential for performance but not a prescription for practice. Significant investment information may often be available for only a relatively small number of stocks in an index or optimization universe. Many managers intuitively understand that they should be investing in a set of assets for which they are best informed. Careful consideration of this issue can have dramatic implications for performance while avoiding ineffective investment strategies.

6.0 Summary and Conclusions

While the essential wisdom of the Grinold "Law" as a theoretical though unattainable upper bound is not controversial, we show that the four active portfolio management principles associated with applications of the formula – frequent trading, large stock universes, adding forecast factors and removing constraints – are generally self-defeating, often invalid, and provide vanishing if any benefits to the investor. Our simulations show that, under realistic conditions appropriate for practice, an equal weighting strategy beats unconstrained, long-only portfolios generally prevail over equal and unconstrained, and, beyond a certain point, the size of the optimization universe is irrelevant. Active investors should invest in what they know but no more.

---

[30] Michaud resampled optimization was invented by Richard Michaud and Robert Michaud and is a U.S patented procedure, #6,003,018; worldwide patents pending. It was originally described in Michaud (1998, Ch. 6). New Frontier Advisors, LLC (NFA) is exclusive worldwide licensee.

[31] Uncertainty level can be defined by a "forecast confidence" scale based on estimation periods as described in Michaud and Michaud (2008a, 2008b) or by the investor's IC.

[32] We note that Michaud optimization is not the same as the Morningstar resampling optimizer which uses a different frontier averaging process with different out-of-sample investment properties. See Michaud and Esch (2010) for further information.

[33] Michaud (1998, Ch. 6), Michaud and Michaud 2008a,b. Markowitz and Usmen (2003) simulation studies indicate that Michaud optimization may be superior to Markowitz even with inferior risk-return estimates.

The definite failure of the Fundamental Law equation when implementing the prescriptions is due to ignored estimation error. The shortfall can be mitigated somewhat with economically meaningful linear constraints for defining portfolio optimality. Much of currently implemented investment theory and applications is based on frameworks that assume known probability distributions and stable returns analogously to a casino game. But investing is not a casino game. Investors always have uncertainty and error in their risk-return estimates in practice.[34]

Unfortunately, the fundamental limitations of the GK and CST principles are widespread in contemporary quantitative asset management and afflict many portfolio strategies. Such principles have been taught in academic and professional journals for many years and likely adversely impact many hundreds of billions of dollars or more in contemporary investment practice.

There are fundamental issues well beyond finance chronicled in this report. Modern science (including finance) has inherited "a serious disconnect between quantitative research methodology and clinical practice."[35] Grinold is only one example of the fundamental and ubiquitous Weisberg (2014) fallacy of regarding inference from fixed probability models as the full measure of uncertainty.[36] For the future, our revisions to the necessary conditions for reliably winning the investment game include: 1) investment significant information for the entire optimization universe; 2) economically meaningful constraints; and 3) properly implemented estimation error sensitive portfolio optimization technology.

[34] Assuming no illegal insider information.
[35] Weisberg (op. cit. p. xii) notes the need to reengineer probability by accounting for some of the complexity that has often been ignored.
[36] Weisberg op. cit., p. xiii.

References

Anson, M., D. Chambers, K. Black, H. Kazemi. 2009. *An Introduction to Core Topics in Alternative Investments* CAIA Association, 2nd ed. 2012. Wiley.

Buckle, D. 2004. "How to Calculate Breadth: An Evolution of the Fundamental Law of Active Portfolio Management." *Journal of Asset Management* 4(6):393–405.

Clarke, R, H. deSilva, S. Thorley. 2002. "Portfolio Constraints and the Fundamental Law of Active Management." *Financial Analysts Journal* 58(5): 48-66.

Clarke, R., H. deSilva, S. Thorley. 2006. "The Fundamental Law of Active Portfolio Management." *Journal of Investment Management*, 4(3): 54-72.

De Silva, H., Thorley, S., & Clarke, R. G. 2006. "The Fundamental Law of Active Portfolio Management." *Journal of Investment Management*, 4(3): 54-72.

Darnell, M. and K. Ferguson, 2014. "Thoughts On Grinold & Kahn's Fundamental Law Of Active Management" First Quadrant Perspective..

Diderich, C. 2009. *Positive Alpha Generation: Designing Sound Investment Processes*, Wiley.

Ding, Z. 2010. "The Fundamental Law of Active Management: Time Series Dynamics and Cross-Sectional Properties." Russell and Thaler Asset Management working paper.

Esch, D. 2015. "Some Notes on Information Correlation: Estimation and Simulation." Working paper, New Frontier Advisors.

Farrell, J. 1983. *Guide to Portfolio Management*. Wiley, NY.

Foquardi, S. and F. Fabozzi, 2004. The Mathematics for Financial Modeling and Asset Management, Wiley.

Frost, P. and J. Savarino. 1988. "For Better Performance: Constrain Portfolio Weights." *Journal of Portfolio Management* 15(1):29-34.

Gorman, L., S. Sapra,, R. Weigand. 2010. "The role of cross-sectional dispersion in active portfolio management." *Investment Management and Financial Innovations*, 7(3):54-64.

Grinold, R. 1989. "The Fundamental Law of Active Management." *Journal of Portfolio Management* 15(3): 30-37.

Grinold, R. and R. Kahn. 1995. *Active Portfolio Management: Quantitative Theory and Applications*. Chicago: Irwin.

Grinold, R. and R. Kahn, 1999. *Active Portfolio Management: A Quantitative Approach for Providing Superior Returns and Controlling Risk*. 2nd ed. New York: McGraw-Hill.

Huij, J. and J. Derwall. 2011. “Global Equity Fund Performance, Portfolio Concentration, and the Fundamental Law of Active Management.” *Journal of Banking & Finance*, 35(1):155-165.

Jacobs, B. and K. Levy, 2008. *Investment Management: An Architecture for the Equity Market*. Wiley

Jobson, D. and B. Korkie, 1981. “Putting Markowitz Theory to Work.” *Journal of Portfolio Management* 7(4): 70-74.

Kahn, R. 1997. “The Fundamental Law of Active Management: Seven Quantitative Insights into Active Management—Part 3,” BARRA Newsletter Winter.

Kroll, B. D. Trichilo, and J. Braun, 2005. “Extending the Fundamental Law of Investment Management (or How I Learned to Stop Worrying and Love Shorting Stocks).” JP Morgan Asset Management white paper.

Ledoit, O., 1997 "Improved Estimation of the Covariance Matrix of Stock Returns with an Application to Portfolio Selection." Working paper. Anderson Graduate School of Management, University of California at Los Angeles.

Ledoit, O., and Wolf, M. 2004a. "A Well-Conditioned Estimator for Large-Dimensional Covariance Matrices". *Journal of Multivariate Analysis*, 88(2): 365-411.

Ledoit, O., and Wolf, M. 2004b. "Honey, I Shrunk the Sample Covariance Matrix". *Journal of Portfolio Management*, 30(1):110-119.

Markowitz, H. 1952. “Portfolio Selection.” *Journal of Finance* 7(1): 77-91.

Markowitz, H., 1959. *Portfolio Selection: Efficient Diversification of Investments*. New York: John Wiley and Sons. 1991. 2nd ed. Cambridge, MA: Basil Blackwell.

Markowitz, H. 2005. “Market Efficiency: A Theoretical Distinction and So What?” *Financial Analysts Journal* 61(5): 17-30.

Markowitz, H. and N. Usmen, 2003. “Diffuse Priors vs. Resampled Frontiers: An Experiment.” *Journal of Investment Management* 1(4): 9-25.

Merton, R. 1987. “Presidential Address: A Simple Model of Capital Market Equilibrium with Incomplete Information.” *Journal of Finance* 42(3): 483-510.

Michaud, R. 1989. “The Markowitz Optimization Enigma: Is Optimized Optimal?” *Financial Analyst Journal* 45(1):31-42.

Michaud. R. 1990. “Demystifying Multiple Valuation Models.” *Financial Analysts Journal* 46(1):6-8.

Michaud, R. 1993. “Are Long-Short Equity Strategies Superior?” *Financial Analyst Journal* 49(6):44-49.

Michaud, R., 1998. *Efficient Asset Management*. New York: Oxford University Press, 2001. First published by Harvard Business School Press.

Michaud, R. 1999. *Investment Styles, Market Anomalies, and Global Stock Selection*. Research Foundation of the Chartered Financial Institute, Charlottesville.

Michaud, R. and R. Michaud. 2005. “Equity Optimization Issues – III: Insignificant Alphas and Heterogeneous Errors.” Newsletter: New Frontier Advisors, Boston, March.

Michaud, R. and R. Michaud. 2008a. *Efficient Asset Management*. 2nd ed. Oxford University Press: New York.

Michaud, R. and R. Michaud 2008b. “Estimation Error and Portfolio Optimization: A Resampling Solution.” *Journal of Investment Management* 6(1):8-28.

Michaud, R. and D. Esch, 2010 “Morningstar vs. Michaud Efficient Frontiers.” New Frontier Advisors Research Paper.

Qian, E and R. Hua., 2004. “Active Risk and Information Ratio.” *Journal of Investment Management*, 2(3):1-15.

Roll, R. 1992. "A Mean/Variance Analysis of Tracking Error." *The Journal of Portfolio Management*, 18(4):13-22.

Schulmerich, M., Y. Leporcher, and C. Eu. 2015. *Applied Asset and Risk Management,* Springer: Heidelberg

Utermann, A. 2013. “The Changing Nature of Equity Markets and the Need for More Active Management” Allianz GI Global Capital Markets & Thematic Research.

Weisberg, H. 2014. *Willful Ignorance: The Mismeasure of Uncertainty*. Wiley: New York.

Zhou, G. 2008. “On the Fundamental Law of Active Portfolio Management: What Happens If Our Estimates Are Wrong?” *Journal of Portfolio Management,* 34(4):26-33

IIJ Institutional Investor Journals

The Voices *of* Influence | iijournals.com

JOURNAL OF TRADING

WWW.IIJOT.COM

SPRING 2016 VOLUME 11 NUMBER 2

Liquidity—*How to Capture a Multidimensional Beast*

PHILIP SOMMER AND STEFANO PASQUALI

Liquidity—*How to Capture a Multidimensional Beast*

Philip Sommer and Stefano Pasquali

Philip Sommer
leads a quant team in the liquidity research group at Bloomberg in New York, NY.
psommer5@bloomberg.net

Stefano Pasquali
is the global head of liquidity research at Bloomberg in New York, NY.
spasquali1@bloomberg.net

In today's new market normal, liquidity has become an increasingly expensive commodity, pushing up trading costs for all market participants. The last decade has highlighted just how inadequate the commonly accepted methodologies are for measuring liquidity. Accordingly, international regulatory bodies, such as the Bank for International Settlements and the Committee of European Banking Supervisors, have moved liquidity risk management and supervision high up the global regulatory agenda, and significant changes to existing liquidity regimes are already under way. Yet, despite its importance, no universally agreed upon and adopted measure or model that adequately captures cost and time to liquidation in bond (over the counter [OTC]) markets currently exists. To fill this gap, we reviewed 40 years' worth of research and summarize our findings in this article.

We start from the classic definition of liquidity and argue that the lack of concordance in definition can be attributed to the lack of consistent methodology that puts these into practice beyond stock markets. Throughout this article, we show that the main problem to overcome is the industry's failure to measure liquidity in bond (OTC) markets based on the same market impact methods that have proven most natural and successful for stock markets. Constrained by the scarcity of transaction data, the industry sticks with second-best measures based on bid–ask spread.

Triggered by the fact that the bid–ask spread widens with size, we examine the market microstructure literature to search for common ground between stock and bond (OTC) markets to make our case. We find that the very rules of limit order book markets already reveal why market impact models are best practice to measure liquidity for stocks and, furthermore, that these models similarly hold true for OTC dealer markets. From that perspective, the main differences between bond and stock markets are frequency of trading and availability of data.

Accordingly, there is a vast literature on market impact models for stock markets. We summarize the main theoretical and empirical results, which show that square-root-shaped models can be attributed to the market microstructure arguments that generally apply similarly for OTC dealer markets. Reviewing the available research on bond markets, we instead find attempts to use asset- or market-related characteristics as proxies in the absence of data and primitive measures where transactional data are made available by post-trade transparency regimes. Summarizing our findings, we claim that, where needed, proxies should be considered in a way that captures all data at the same time and in light of dynamic market conditions.

Taking a closer look at research that expands round-trip cost to price dispersion measures, we discover parallels to market impact measures and generalize that (transaction) price uncertainty distributions and liquidity are in essence two sides of the same coin in bond (OTC) markets. Looking more closely at what drives transaction price uncertainty, we find two things that need to be further examined: First, the literature on liquidity crises suggests that market liquidity, funding liquidity, and monetary liquidity interact in a way that can frequently lead to downward-spiraling market conditions. Although this similarly holds true in equity markets, it can lead to more excessive polarization of market liquidity in bond markets. Second, reviewing the literature on frictions in OTC markets, we find further complexity explaining the fact that bonds can trade at different prices at approximately the same time.

Put simply, the complexities that differentiate OTC dealer markets from equity markets do not motivate substantially different approaches in measuring liquidity. Instead, complexities will be captured as different levels of uncertainty inherent in any attempt to measure liquidity in both markets using a consistent framework.

In conclusion, we suggest that machine learning methods are the most natural candidates to overcome the main obstacles we summarize in this article, as they can help extract desired information from the extremely sparse data that serve as the main difference between equity and bond markets. Such an approach can build on existing research and incorporate all relevant proxies simultaneously to better capture multidimensionality and provide the interpretability needed by market practitioners and regulators.

As we show throughout this article, this approach would allow us to put a framework that measures liquidity consistently across asset classes into play. Connecting the dots within the vast body of literature, we find that the key ingredients of such a novel approach would be to take market impact models as a natural starting point and employ the necessary calculations to quantify the inherent uncertainty of such a measure. Evidencing that this works in practice can facilitate agreement on a definition of liquidity by providing a consistent methodology that puts the same measures into practice for fixed income (OTC) and stock markets. The development of a methodology along the guidelines outlined will be the subject of a forthcoming paper.

DIGGING DOWN TO THE ROOTS—WHAT WE CAN LEARN FROM TRADITIONAL VIEWS ON LIQUIDITY

Fischer Black [1970] first explored the notion of a trade-off between liquidity and return, but it was not until he met Jack L. Treynor that this concept reached a mature form—the understanding that liquidity is not about value; it is about price.

Treynor's idea (Bagehot [1971], Bagehot being Treynor's pseudonym) was that market liquidity depends first on the ability and willingness of dealers to absorb temporary imbalances in the flow of supply and demand by using inventories on their own balance sheets as a buffer. However, the ultimate source of liquidity is the value investor who is willing to take those inventories off the hands of the dealer when the price moves far enough away from value. One of the main conclusions of this view is that price has to move away from value in order to attract buyers and sellers, and this distance can be thought of as determined by a liquidity factor. The vast body of literature on liquidity shows that this liquidity factor is influenced by a wide range of elements, such as asset characteristics, market conditions, and market imperfections (frictions)—hence we talk of it as a multidimensional beast.

Mehrling [2011] found that during the 2008–2009 global financial crisis, the liquidity factor played a much more prominent role not just in driving the price of assets away from fair value, but also in disrupting the funding of asset positions. In the end, it is the liquidity factor that drove the shadow banking system onto the balance sheet of the government, and it is the liquidity factor that is keeping it there.

Building on Black's [1970] early work, Grossman and Miller [1988] suggested immediacy was the essence of liquidity, and Harris [1990] proposed that liquidity be defined through four interrelated dimensions:

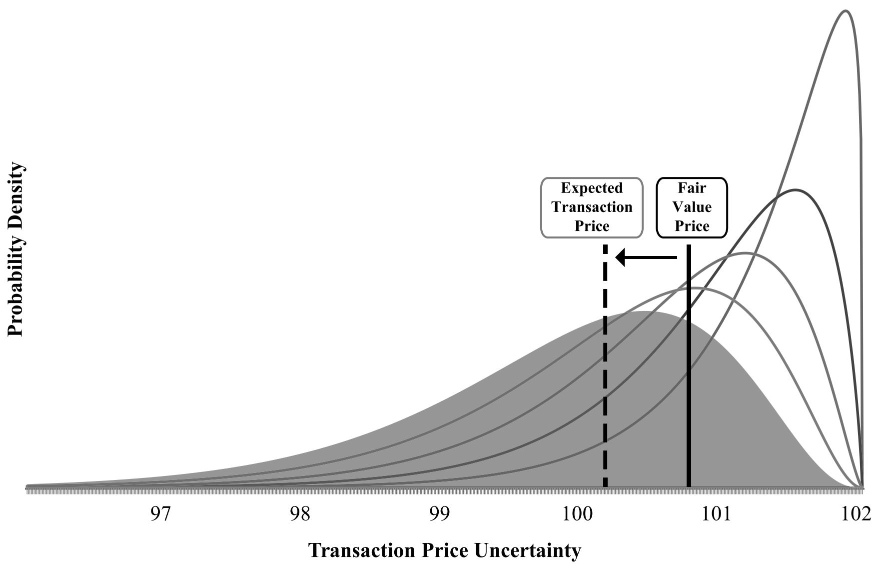
- **Width**, typically captured by the size of the bid–ask spread, which measures the cost of consuming liquidity immediately, but does not capture the quantity that can be traded at that spread;
- **Depth**, the quantity of liquidity supplied, typically measured by the volume offered at the bid–ask spread;
- **Immediacy**, how quickly a large trade can be accomplished; and

- **Resiliency**, how long it takes for the price to return to the pretrade equilibrium after a large trade consumes liquidity.

Two decades after Harris's [1990] publication, the European Banking Authority (EBA) [2013] suggested this classification still provides a useful guide for a set of measures covering the most important aspects of liquidity and pointed to the consequent need to assess liquidity across different dimensions simultaneously.

We can derive two key lessons from these attempts to define liquidity. First, liquidity drives a wedge between value and price. Following Black's [1970] argument, the natural definition and basis of measuring liquidity would be the price to be paid above or below fair value to attract a counterpart willing to transact in a given timeframe and market condition (see Exhibit 1). Second, the wedge between price and value has to be modeled in a way that captures the multidimensionality of the liquidity factor.

EXHIBIT 1
Liquidity can Drive a Wedge Between Value and Price



Note: The cost of liquidation is the price to be paid above or below fair value to attract a counterpart willing to transact a specific position size in a given time frame and market condition.

INVENTORY RISK—THE BID–ASK SPREAD WIDENS WITH SIZE

As Amihud and Mendelson [1991] found, investors prefer to commit capital to liquid investments that can be traded quickly and at low cost whenever the need or wish arises. Assets that are less liquid must therefore offer a higher expected return to attract investors.

The role of market makers is to provide liquidity by taking the opposite side of a transaction, or as Treynor suggested, to absorb temporary imbalances in the flow of supply and demand by using inventories on their own balance sheets as a buffer. This notion introduces another key aspect when it comes to liquidity: *inventory risk*.

The inventory function exposes market makers to the risk of an adverse price move from the point at which a dealer buys an asset until the point at which the asset can be offloaded into the market again. The longer a market maker has to hold those assets, and the less predictable the price of those assets is, the greater the price uncertainty the market maker has to consider regarding the round-trip transaction. Thus inventory risk, price uncertainty, and liquidity are inextricably linked.

Demsetz [1968] was the first to justify the existence of the bid–ask spread as a compensation for providing liquidity to those who seek it. Grossman and Miller [1988], however, suggested that an investor desiring to sell is likely to be more concerned with how the bid price will change over time than with the size of the current bid–ask spread.

Glosten [1989] argued that well-informed traders maximize the returns they can achieve from having an information advantage over a dealer (i.e., knowing something the dealer does not). For market makers, large trades therefore suggest that an investor is benefiting from better information, and the bid–ask spread should consequently widen. The spread is therefore a function of trade size. Glosten [1989] concluded that studies aiming to derive the relationship between expected returns and liquidity should examine not only the width of the spread for a typical trade size, but also how this changes as trade size increases.

The literature suggests the shape of this relationship can be traced back to the very basic defining properties of markets.

MARKET MICROSTRUCTURE—THE RULES OF THE GAME DEFINE ITS OUTCOME

Foucault, Pagano, and Roell [2013] explored how features of market design, such as transparency, fragmentation, and limit order trading, affect measures of market performance—in particular, liquidity, speed of price discovery, and the distribution of gains from trade among market participants.

A trading mechanism defines the *rules of the game* market participants must follow: This mechanism determines the actions participants can take (e.g., the kind of orders they can place), the information they have about other market participants' actions (e.g., whether they observe quotes or orders), and the protocol for matching buy and sell orders (e.g., whether or not orders are executed at a common price).

Essentially, two kinds of trading mechanisms exist: *limit order markets* and *dealer markets*. In limit order markets, which are the dominant structure for trading equities, final investors interact directly, and a marketplace of orders is consolidated and ranked on the basis of price on a platform such as an electronic limit order book (LOB). Orders go into the LOB, which determines the priority with which they are matched against offsetting orders.

EXHIBIT 2
Example of Limit Order Book

Market sell order of 200 (or limit sell with price < 74.42)

Market buy order of 900 (or limit buy with price > 75.74)

Bid			Ask		
Price	**Size**	**Time**	**Price**	**Size**	**Time**
74.42	~~300~~ 100	11:49:39	74.48	~~300~~	11:49:35
74.41	100	11:46:55	74.48	~~500~~	11:49:40
74.36	400	11:48:30	75.74	~~100~~	08:25:17
74.36	400	11:48:32	76.00	150	08:02:02
74.00	13	10:56:00	76.77	20	07:01:01
73.75	S100	11:28:02	77.00	100	09:15:00
72.98	S100	10:56:99	77.06	200	10:14:11
72.15	120	08:01:39	77.35	1000	08:01:39
72.11	20	07:01:01	77.82	20	07:01:01
72.03	20	07:01:01	78.00	300	08:02:00
72.00					9:30:04
71.59					8:01:32
71.11					9:30:04
71.00					7:01:01
70.35					8:01:35
70.11	20	07:01:01	80.00	350	09:15:00

Because of the buy market order, the bid-ask spread windens from 74.48 – 74.42 = **0.06** to 76.00 – 74.42 = **1.58**

The market order has "consumed" liquity.

Source: Foucault, Pagano, and Roell [2013].

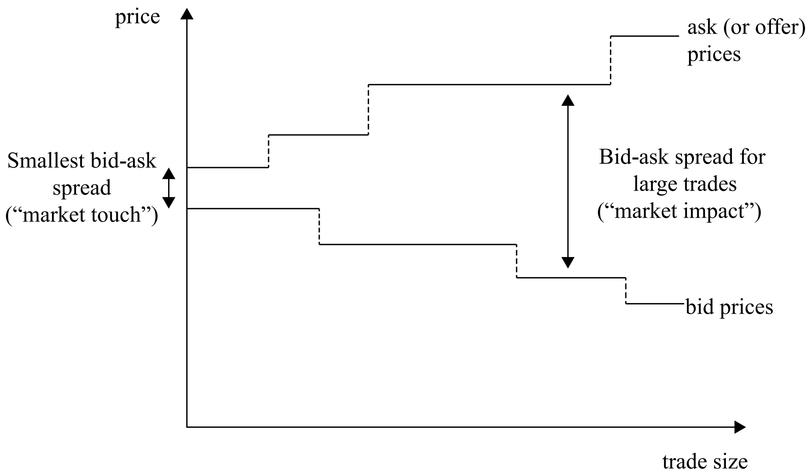
The LOB shown in Exhibit 2 illustrates the mechanics of trading in a continuous limit order market. The LOB can also be used to illustrate the notion of illiquidity: If the market were perfectly liquid, the cost of a round-trip transaction would be zero. Instead, Exhibit 2 shows that trading has a positive cost that increases with size, because the buyer/seller has to walk up/down the schedule of buy/sell limit orders to meet the desired transaction volume.

In dealer markets, the final investors do not trade directly with each other. Instead, they must contact a specialized intermediary—a dealer or market maker—to find out the intermediary's price and then either trade at that price or try another dealer. Thus, in a dealer market there is a sharp distinction between liquidity suppliers (dealers) and liquidity demanders (final investors), whereas in a limit order market each participant chooses whether to provide or demand liquidity.

Dealers' quotes are typically valid for only a limited volume and a short period of time. A large order may be executed by splitting it among several dealers. In that case, effectively, a seller/buyer is walking down/up the demand/supply curve resulting from the aggregation of dealers' bid–ask quotes. These aggregated demand and supply curves are shown in Exhibit 3. Consequently, in a dealer market, as in a limit order market, one can also define a weighted-average bid–ask spread that is, of course, also increasing in trade size.

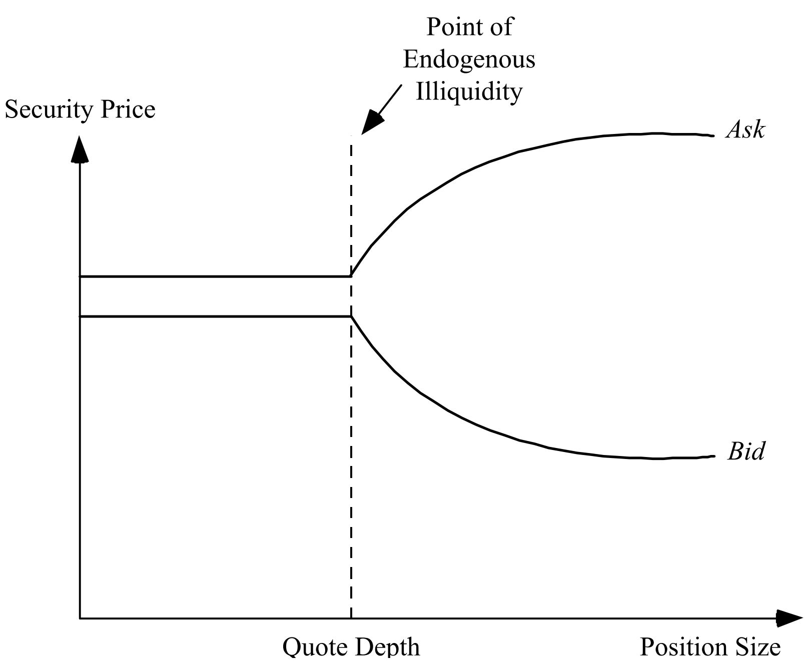
Connecting the dots in the literature, the rules of the game determine the relationship between volume and price. Even though there are significant differences between limit order and dealer markets, the way liquidity should be looked at is largely similar and can be stylized along the lines of Bangia et al. [2001], who drew this relationship as a concave (for bid prices) or convex (for ask prices) market impact curve. In reality, the curve is not as simple as Exhibit 4 would suggest. In all market-impact curves, there is a trade size beyond which dealers or market makers are increasingly unwilling to carry the inventory risk associated with taking the opposing side of the trade. Where that point is reached, there is a *liquidity cliff*, beyond which the price to be paid for obtaining liquidity must accelerate in order to attract market participants willing

EXHIBIT 3
Dealer Market Quotes for Various Trade Sizes



Source: Foucault, Pagano, and Roell [2013].

EXHIBIT 4
Market Impact and Concave/Convex Price Curves—the Effect of Position Size on Liquidation Value



Source: Bangia et al. 2001.

to transact at such large volumes (see Exhibit 5). Typically, in this territory, the group of potential counterparts consists of distressed asset players, such as hedge funds. Even beyond the liquidity cliff, the price of some assets will never reach zero. Instead, they level off, as shown in Exhibit 5.

Mehrling [2010] provides a good explanation for this in his discussion of how, in a severe crisis, market liquidity is no longer a matter of the funding liquidity of private dealers, but instead of shiftability to the Federal Reserve (Fed). If an asset is not shiftable to the central bank, it may not be shiftable at all, or only at an unacceptably large price discount. In a crisis, the central bank is therefore not so much the lender of last resort as it is the dealer of last resort.

In summary, liquidity risk analysis should involve estimates of the market impact curve, in particular how it steepens beyond the point of quote depth and where the liquidity cliff is situated, so risk managers can capture better the potential cost of trading.

MODELING THE SHAPE OF THE MARKET IMPACT CURVE

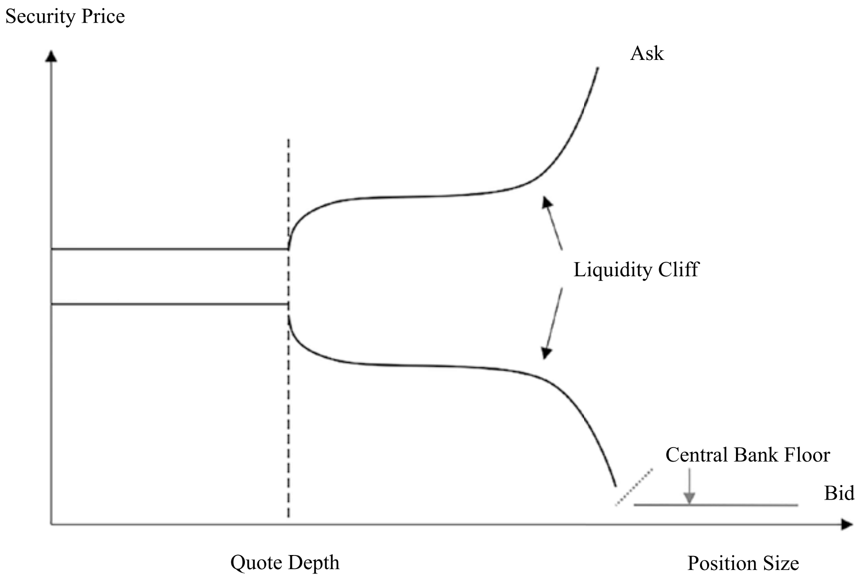
There is a vast body of literature on modeling market impact curves in equity markets, from which we can draw when constructing comparable models for OTC markets. For example, Perold and Salomon [1991] argued that the liquidity premium per share will be either a convex or a concave function of block size, depending on whether the market perceives the trader to be information-driven or liquidity-driven, respectively.

To estimate the degree of convexity or concavity, the square-root formula has been widely used to generate a pretrade estimate of transaction cost, as it fits the data remarkably well. Furthermore, as noted by Grinold and Kahn [1999], it is consistent with the trader rule of thumb that trading one day's volume costs roughly one day's volatility.

From the broader perspective, Almgren [2003] took the market impact cost per share to be a power law function of the trading rate or block size, with an arbitrary positive exponent. Almgren laid the foundation for the optimal execution literature—in particular, the price process model developed distinguishes between a temporary and a permanent market impact. The former is liquidity driven

EXHIBIT 5

Different parts of a liquidity model: best bid-ask, market impact curve, liquidity cliff and central bank floor



and affects the price only for a period of time, whereas the latter is information driven and affects the price permanently. Needless to say, this partition is idealized and extreme.

Almgren et al. [2005] subsequently provided a quantitative analysis of market impact costs based on a large dataset from the Citigroup U.S. equity trading desks. Using a simple but realistic theoretical framework, they fit the model across a wide range of stocks, determining the coefficients' dependencies on parameters such as volatility, average daily volume, and turnover. Interestingly, the authors rejected the common square-root model for temporary impact as a function of trade rate in favor of a three-fifths power law across the range of order sizes considered. That paper provided empirical confirmation of Huberman and Stanzl's [2004] theoretical arguments in favor of a permanent impact with linear block size and a concave temporary impact, as has been widely described in the literature for both theoretical and empirical purposes.

By analyzing individual trade data, Bouchaud et al. [2004] realized that trade signs display a long-range correlation, a fact in contradiction with the random walk nature of prices. To resolve the contradiction, Bouchaud et al. [2004] introduced the concept of *transient market impact*—that is, a market impact that fades over time. In the transient market impact framework, the "memory" of the market is modeled by a propagator function, which describes the effect of all past trades on the price process. In a subsequent paper, Eisler, Bouchaud, and Kockelkoren [2012] extended the propagator approach to model all the possible order book events occurring at the first level of the order book (the best bid and best ask). Their results showed that the direction of incoming limit orders is negatively correlated with that of market orders. The decay of impact of a single order is thus a consequence of the interplay between liquidity providers and liquidity takers. Gatheral [2010] proposed a continuous time version of the propagator model, adapted to optimal execution.

Further Explaining Square-Root Shape and the Market Impact Curve

Toth et al. [2011] proposed a dynamic theory of market liquidity that relies on two things: mild assumptions about the order flow and the fact that prices are (to a first approximation) diffusive. They started with the intuition that available volume grows as price excursions become larger, leading them to propose that average supply (or demand) is a V-shaped curve that vanishes around the current price.

They expanded on this theory with the idea of a *latent order book* that, at any point in time, aggregates the total intended volume for sells at or above a given price (p) and the total intended volume for buys at or below that given price. The authors emphasized that this is generally not the volume revealed in the real (observable) order book, but rather the volume that would reveal itself in the order book, or as market orders, if the real price came instantaneously closer to the given price (p). However, because there is little incentive to reveal one's intentions too early, most volume is latent and not revealed. Based on this framework, Toth et al. [2011] showed that the universally observed concave impact law is a consequence of some robust, generic assumptions about market dynamics.

The most important message from Toth et al.'s [2011] theory is the critical, inherently fragile nature of liquidity. A diffusive price necessarily leads to the vanishing of liquidity in the vicinity of the current price. This naturally accounts for two striking stylized facts: First, large metaorders have to be fragmented to be digested by the liquidity funnel, leading to long memory in the sign of the order flow. Second, the anomalously small local liquidity induces a breakdown of linear response and a diverging impact of small orders, thereby explaining the square-root impact law. Moreover, liquidity fluctuations are bound to play a crucial role when the average liquidity is small. Toth et al. [2011] expected these fluctuations to be at the heart of the turbulent dynamics of financial markets.

The empirical studies on market impact that have accumulated over the years differ significantly in terms of how price impact is defined and measured, how different assets and periods are collated together, and how the fit is performed (see, for example, Almgren et al. [2005], Ferraris [2008], and Engle, Ferstenberg, and Russell [2012].) Yet, in spite of all these differences, it is remarkable that the square-root impact law appears to hold approximately in all cases.

Although the literature summarized in this section is concerned with equity markets, in the absence of comparable results for the bond market and given the relevance of the market impact model to both limit order- and dealer-based trading mechanisms, it would be reasonable to use the results as orientation for the construction of a market impact model for bond markets.

Bond (OTC) Markets Are More Difficult to Model

The different levels of transparency in equity and bond markets mean market impact models are not as easily formulated for the latter as they are for the former. While transaction prices and volumes are made available by exchanges, fixed income markets are significantly less transparent and, moreover, bonds are generally traded with slower turnover. As a consequence, market participants rely on a variety of proxies to gauge the liquidity of particular markets or securities. However, none is good enough on its own, and the more factors a model can capture, the more accurate the picture of liquidity it produces will be. As Amihud [2002, p. 35] pointed out, typically, measures of liquidity "can be regarded as empirical proxies that measure different aspects of illiquidity. It is doubtful that there is one single measure that captures all its aspects."

THE BASEL COMMITTEE DEFINITIONS

The Basel Committee [2013] laid out a set of general characteristics that are used to define high-quality liquid assets (HQLA) in Basel III. This is particularly important given that the demand for liquidity measures is also driven by the regulatory agenda, and the Basel definitions frame the general perspective for the industry. These definitions state that, in order to qualify as HQLA, assets should be liquid in markets during a time of stress and, ideally, central bank eligible. Assets are considered to be HQLA if they can be easily and immediately converted into cash at little or no loss of value.

The Basel Committee [2013] specifies the factors that define an HQLA as the following:

- **Fundamental characteristics**: Low risk (high credit standing of issuer and low subordination, low duration, low legal risk, low inflation risk, and denomination in a convertible currency with low foreign exchange risk), ease and certainty of valuation (a higher degree of agreement on valuation is likely with more standardization, homogeneity, and simplicity of products), low correlation with risky assets, and listing on a developed and recognized exchange.
- **Market-related characteristics**: Active, sizeable market (low bid–ask spreads, high trading volumes, large and diverse number of [committed] market participants), low volatility (prices and volumes during stressed periods), and flight to quality (assets typically sought in times of systemic crisis).

Overlaying empirical research with the Basel Committee's [2013] definition, most of the typical proxies used to measure liquidity fall into these two categories. In addition, some basic liquidity measures may be used when the necessary data are available by means of post-trade transparency regimes such as the Trade Reporting and Compliance Engine (TRACE) or, in the future, the Markets in Financial Instruments Directive II (MIFID II).

ASSET CHARACTERISTICS AS PROXIES

According to Friewald, Jankowitsch, and Subrahmanyam [2012], product characteristics are crude proxies for liquidity that rely on the lowest level of information detail. Consequently, they are typically applied when the level of available information is severely limited.

Jankowitsch, Nashikkar, and Subrahmanyam [2011] suggested that the most important indirect, bond-specific proxies are the amount issued, maturity, age, rating, bid–ask spread, and trading volume. Other literature broadly supports this view, and there is some consensus on typical patterns. For example, Dastidar and Phelps [2009] confirmed the common sense that liquidity increases as issue size and trading volume increase and excess return volatility decreases. However, Acerbi and Scandolo [2007] pointed out that there is no magic formula for these characteristics, and findings vary across market segments, such as government bonds versus corporate bonds and investment-grade versus high-yield bonds.

- **Credit quality**: The European Banking Authority [2013] suggested that credit quality is closely linked to liquidity because assets of low credit quality typically have greater information asymmetries and thus larger bid–ask spreads. Jankowitsch, Nashikkar, and Subrahmanyam [2011] and Vasvari [2011] further supported the case for the lower liquidity of lower credit quality bonds, something also assumed by most market participants. The literature suggests this variable is mainly driven by the difference between investment- and speculative-grade corporate bonds as trading activity declines with ratings and falls off significantly below investment grade. Interestingly, the Basel Committee's [2013] definition looks at risk more broadly (as discussed previously).
- **Maturity**: Generally, the longer the maturity of a bond, the higher the associated overall risk. It follows that liquidity is expected to fall as time to maturity increases. Several studies (including those by Dick-Nielsen, Feldhütter, and Lando [2012], and Feldhütter [2012]) support this notion, although the degree to which liquidity changes varies across the findings. There is, however, evidence in the literature suggesting the relationship is not so clear cut and is affected by the market conditions (demand patterns change in periods of market stress), recent activity (such as a buyback less than a year previously), and age, thus demonstrating that maturity on its own is not an accurate proxy for liquidity.
- **Amount issued**: Houweling, Mentink, and Vorst [2005] found that many papers consider the amount issued as a proxy for liquidity because the larger the amount of a bond issued, the greater the number and type of investors who will hold allocations of those bonds, leading to higher liquidity. In contrast, smaller bonds tend to be locked in buy-and-hold portfolios more easily. Although research on Treasury bonds seems to confirm this finding, McGinty [2001] suggested this link may not be so strong for corporate bonds. Overall, the empirical research shows there is a relationship between amount issued and liquidity, albeit not a very powerful one on its own.
- **Age**: The age of a bond is a popular proxy for its liquidity given the assertion (which is extensively supported in the literature by, for example, Sarig and Warga [1989], Schultz [2001], Houweling, Mentink, and Vorst [2005], and Vasvari [2011]) that as bonds age, less trading takes place and liquidity falls. Furthermore, these bonds are likely to remain illiquid until maturity because they are locked in buy-and-hold portfolios. Jankowitsch, Nashikkar, and Subrahmanyam [2011] confirmed this relationship but suggested it is better explained in the context of *on-the-run* versus *off-the-run* bonds—the most recent issue is likely to be more popular than an older bond covering the same period. Overall, the available research comes to different conclusions as to where (and why) to draw the lines between young and old, further indicating that proxies should be seen as aspects of a multidimensional interaction.
- **Duration, coupon rate, term to maturity, and price volatility:** Dastidar and Phelps [2009] explained the link between liquidity and duration times spread (DTS) based on the rationale that DTS measures excess return volatility, which contributes to inventory risk. Duration, coupon rate, term to maturity, and price volatility are highly interrelated factors. Accordingly, greater excess volatility is expected to impair liquidity and should be proxied by considering all of these aspects at the same time.
- **Exogeneities such as central bank eligibility**: Some external factors can play an important role in determining the liquidity of an instrument. The EBA Banking Stakeholder Group [2013] found, for example, that an asset's liquidity can be significantly increased by the certification effect of institutional recognition (e.g., classification as an HQLA under the Basel III framework). Central bank eligibility is an important liquidity driver, as it ensures that assets can be converted into cash without an actual sale. In

fact, this eligibility is likely the main liquidity criterion for many market participants, so its role should not be underestimated. This factor can be self-fulfilling—something that is certified can become more liquid as traders and dealers take comfort in the certification—and regime changing, creating significant fundamental shifts in liquidity.

Essentially, all of these factors have one thing in common: They represent risk. With that risk, price uncertainty increases and, as a consequence, inventory risk increases and liquidity falls. Although all of these factors affect the liquidity of an asset and can be used as a proxy for liquidity to some degree, none is a holy grail for measuring liquidity on its own.

Market-Related Characteristics as Proxies

Beyond fundamental characteristics, further useful information can be found at the market level. However, the same issues exist. No characteristic is good enough as a standalone measure. Furthermore, during periods of market stress, these proxies break down as their link to liquidity becomes misleading.

For example, several studies (including those by Aitken and Comerton-Forde [2003] and Fleming [2003]) found that market activity gauges may falsely signal high liquidity in times of crisis. Although the cost of obtaining liquidity in periods of stress may be high (wide bid–ask spreads, large price impacts, etc.), investors are still willing to accept these high transaction costs to liquidate or rebalance positions. For instance, in November 2008, heavy selling by investors in an illiquid market led to very high volumes, showing that volume alone is not a strong proxy for liquidity but instead needs to be looked at in conjunction with transaction prices.

Comparable arguments and limitations are likely to hold for most market activity variables that can be used as proxies:

- **Volume, turnover**: Volume, or a scaled version of volume, is widely used as a proxy, based on the common thinking that more active markets tend to be more liquid. Johnson [2007] explained further that, from the perspective of standard market microstructure models, higher transaction demand should lead competitive liquidity providers to offer cheaper services, and cheaper trading should elicit more trades. Subsequently, he demonstrated that this intuition largely fails in time-series data. Instead, he offered a slightly different implication: Volume is positively related to liquidity risk. Benston and Hagerman [1974], among others, showed that trading volume is correlated to volatility, which can impede market liquidity and gives further evidence that transaction volume and prices need to be looked at in unison. In addition, volume-based approaches fail to capture instances in which bonds that seldom trade are, in fact, highly liquid. An example for this latter situation is any highly attractive bond which is so appealing to buy-and-hold investors that it rarely trades. In those cases, selling would likely prove to be quick and easy with little or no discount required.
- **Quoted bid–ask spread**: The bid–ask spread is a commonly used proxy for liquidity. Among others, Dastidar and Phelps [2009] chose to define liquidity merely as a function of the bid–ask spread. They mainly did this because of the ease of data availability and because many market participants believe the bid–ask spread is likely to be highly correlated with other liquidity measures, such as market impact measures. However, there are two obvious shortfalls: First, available bid–ask spread data are often based on indications, rather than firm commitments, to make markets at those levels; second, the bid–ask spread is only useful for small trades that fit within the quoted depth. Once the depth is breached, however, this becomes inconclusive as a gauge of liquidity on its own. At this point, market impact models are a much more meaningful measure. This is precisely because, as previously discussed, bid-ask spread is widening as trade size increases.
- **Market breadth**: Gehr and Martell [1992] and Jankowitsch, Mösenbacher, and Pichler [2002] argued that a larger number of market participants makes it easier to trade a bond because it is easier to find a counterparty for a transaction, and large orders can be split into smaller parts without affecting the market price. The European Savings Banks Group [2013] suggested that the presence of a large number of market makers in stable times does not necessarily imply they will stand ready to ensure that the instruments are also liquid under turbulence. Consequently, what matters is not the number of market makers, but rather their pricing and risk-taking capacity in a

specific moment. As the latter cannot be measured reliably by market breadth, breadth can only provide limited qualitative indications.

Basic Liquidity Measures

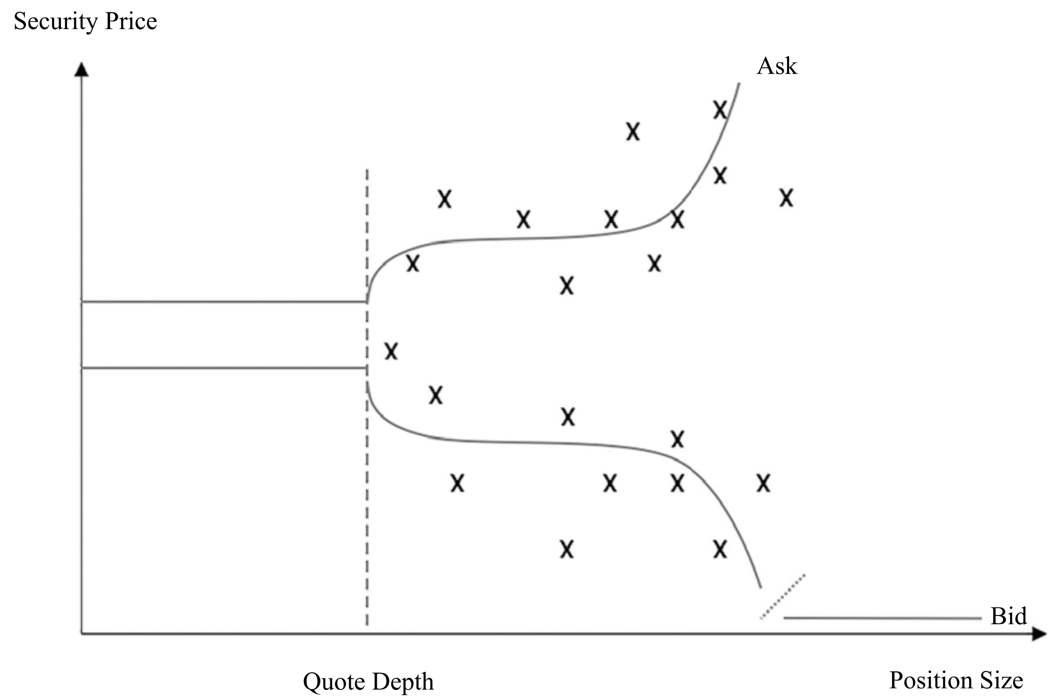
A current topic of discussion is how much transparency should exist around trading data for the smooth functioning of markets. Security Market regulation, such as MIFID II, is closely focusing on how deep transparency should go.

Friewald, Jankowitsch, and Subrahmanyam [2012] explored the relationship among the various measures and proxies for liquidity and the depth of trading data dissemination. They found that measures digesting transaction prices and volumes contain significant idiosyncratic information and as such can provide higher explanatory power over proxies based on asset- or market-related characteristics alone. The dissemination of transaction prices and volumes of each individual trade thus is important to quantify liquidity. However, the authors also found evidence that compromising dealer identity does not shed significantly more light on liquidity measures. Buy/sell flags are still useful, as related estimation (described, for example, by Lee and Ready [1991]) is imperfect:

- **Effective bid–ask spread**: According to Foucault, Pagano, and Roell [2013], the effective bid–ask spread can be seen as the measure of a transaction's impact on price, since it measures the actual execution price's deviation from the midprice prevailing just before the transaction. The impact is positive precisely because the liquidity of the market is limited. An effective bid–ask spread thus tries to overcome the inherent shortcomings of quoted bid–ask spreads by blending in actual transaction data. This improvement, however, comes at the cost of providing a retrospective measure of liquidity.
- **Roll measure**: Roll [1984] found that under certain assumptions, the effective bid–ask spread can be extracted from consecutive returns. Building on Roll's [1984] work, Friewald, Jankowitsch, and Subrahmanyam [2012] found that, in the context of OTC markets, adjacent price movements can be interpreted as a *bid–ask bounce* resulting in transitory price movements that are serially negatively correlated. The strength of this covariation is that it serves as a proxy for the round-trip transaction costs of a particular financial instrument, and hence, as a measure of its liquidity. The German Banking Industry Committee [2013] suggested that, although in theory Roll's [1984] measure provides an estimator for effective bid–ask spreads, it relies on assumptions that are arbitrary in practice. Furthermore, Roll's [1984] model fails to eliminate the actual daily bond price fluctuations (triggered, for instance, by a strong movement of the yield curve), which could also distort the results considerably.
- **Round-trip cost/imputed round-trip cost**: This measure accounts for the price difference a given trader would pay to complete a full cycle of buying (or selling) a certain amount of a security and subsequently selling (or buying) the same amount within a particular timeframe. Expanding on the concept, Feldhütter [2012] proposed an imputed round-trip trades (IRT) measure of transaction cost. Surprisingly often (20% of all trades disseminated in TRACE) a corporate bond trades two (or three) times within a very short period after a longer period with no trades. This is likely to occur because one (or two) dealer(s) matches a buyer and a seller. In other words, if two or three trades with the same trade size take place on the same day in a given bond, and there are no other trades with the same size on that day, we define the transactions as part of an IRT. Again, the round-trip cost tries to address the shortcomings of the quoted bid–ask spread; however, the limited applicability of the measure equally limits its usefulness.
- **Price-dispersion measures**: Trying to overcome the limitations of Roll's [1984] measure and IRT, Dick-Nielsen, Feldhütter, and Lando [2012] and Feldhütter [2012] suggested that measuring the dispersion of consecutive transaction prices can be a useful measure of liquidity. The rationale behind this is that, given enough transaction data observations, market depth can be inferred. For example, when a large amount of transaction data across a range of different volumes shows little dispersion, this suggests that market depth, and thus liquidity, is high. Alternatively, when there is greater dispersion, this suggests less market depth, and the instrument is likely to be less liquid. In other words, the dispersion of prices comprises an imperfect empirical realization of the market impact curve and thus gives an approximate idea of its shape (see Exhibit 6).

Exhibit 6

Price Dispersion Can Reveal an Imperfect Realization of the Market Impact Curve



Bushman, Le, and Vasvari [2010] only included trading days on which at least four separate transactions were observed and the maximal price was economically distinct from the minimal price. As such, the measure gauges how dispersed trades are throughout the day. Jankowitsch, Nashikkar, and Subrahmanyam [2011] introduced a price-uncertainty measure based on the dispersion of traded prices around a consensus valuation. This measure is defined as the root mean squared difference between the traded prices and the respective market valuation weighted by volume. Their measure is an estimate of the absolute deviation, and, more importantly, interprets the volatility of the price dispersion. The authors' analysis at the level of the aggregate market as well as at the bond level showed that this price dispersion is significantly larger than quoted bid–ask spreads and shows more variation across bonds, providing further evidence that quoted bid–ask spreads are a limited proxy for liquidity in corporate bond markets.

The basic liquidity measures outlined in this section, in particular the effective bid–ask spread and round-trip cost, are useful proxies, but in reality, their applicability is limited by availability of data. Dispersion-based approaches have broader applicability and, at the same time, suggest to think of liquidity and price uncertainty as two sides of the same coin. This naturally builds on the concept of market impact curves and, as will be discussed later in this article, extends beyond market microstructure by incorporating further complexities around market inefficiencies, or *frictions*.

Taking this analysis a step further, we suggest thinking of liquidity as a distribution of transaction prices in a probability density space. Ultimately, liquidity can be expressed as the probability of liquidating a given volume of a security at its fair value price or better in a given time frame and market condition.

MARKET CONDITIONS, THE BUSINESS CYCLE, AND LIQUIDITY CRISES

Market conditions play an important role in determining the price at which a given volume of assets can be liquidated. Amihud, Mendelson, and Pedersen [2012, p. 185] vividly illustrated this concept and how liquidity crises create downward price and liquidity spirals:

> A liquidity crisis is a situation where market liquidity drops dramatically as dealers widen

bid–ask spreads, take the phone off the hook, or close down operations as their trading houses run out of cash and take their money off the table, security prices drop sharply, and volatility increases.

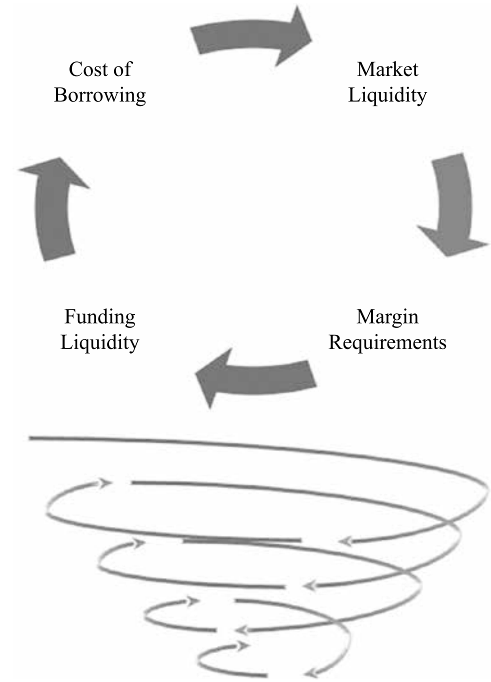
In the following, we will review and summarize the key findings the literature has to offer.

Chordia, Roll, and Subrahmanyam [2000] analyzed commonality in liquidity by examining linkages between particular securities and industries as well between markets as a whole (e.g., stock and bond markets). Unsurprisingly, they found that individual liquidity measures move with each other. Studying such comovement can help to facilitate understanding of macro views of market- and industry-wide liquidity.

Analyzing cross-sectional data, Eisfeldt [2004] found that highly productive industries and economies are associated with more liquid asset markets. Moreover, she showed that market liquidity appears to vary with the state of the economy. This is evident in the variation in spreads between liquid and illiquid assets over the business cycle and in the fact that liquidity crises are associated with economic downturns.

Brunnermeier and Pedersen [2009] provided a theory explaining the origins and underlying dynamics that drive a liquidity crisis. This theory distinguishes between two kinds of liquidity: market liquidity and funding liquidity. Their research found that these two kinds of liquidity interact, which creates liquidity spirals: When traders have good funding liquidity, they can trade more often, which improves market liquidity. In contrast, when constrained, market makers must limit the size of the positions they take on and will increase the price of their liquidity services, which translates into higher transactional cost. Interestingly, just as funding affects market liquidity, market liquidity also affects funding: Favorable market liquidity and lower volatility make it easier to finance traders' positions, lowering their margin requirements. Thus, market liquidity improves funding liquidity and vice versa in a positive feedback loop that creates the potential for a credit boom in good times. This two-way interaction works in reverse during a downturn, and potentially more violently because institutions are forced to carry out fire sales and even default when they cannot meet margin requirements. In turn, liquidity spirals evolve as worsening market liquidity leads to worsening funding liquidity, and so on, until a new equilibrium is reached (see Exhibit 7).

E X H I B I T 7
The Drivers of Liquidity Spirals



Brunnermeier and Pedersen [2009] further showed that such liquidity spirals induce fragility in the financial system, because a shock to one market can have a disproportionate effect as the spiral spreads throughout the financial system, affecting other markets. Therefore, this theory can explain why there is a link between the market liquidity of different securities (*commonality of liquidity*): because the market liquidity of all securities depends on the funding liquidity of banks, market makers, and traders. The theory also helps explain the phenomenon of flight to quality and of asset prices that trade at fire-sale prices during a funding crisis and later rebound.

Adding well to this viewpoint, Petrella and Resti [2013] found that bond characteristics such as rating, issue size, and duration not only affect liquidity significantly but increasingly do so in times of turmoil, as liquidity drivers act nonlinearly under stress, creating a compounding effect in a crisis. From this perspective, liquidity crises can polarize liquidity at the individual bond level; consequently, typical noncrisis correlations/linkages among liquidity, asset, and market-related proxies will break down during periods of stress.

Amihud and Mendelson [2012] summarized their findings as the following: Although the global financial crisis vividly showed that market liquidity can suddenly deteriorate dramatically, the general point is that liquidity is not constant. Rather, liquidity changes over time for individual securities and for the market overall. The authors concluded that the liquidity crises of 1987, 1998, 2005, 2007, 2008, and 2010 clearly illustrate how real-world liquidity risk leads to a drop and rebound of illiquid securities as capital becomes tight and comes back over time, more slowly in more illiquid markets. Exhibit 8 shows how worsening market conditions in liquidity crises are reflected in a shortening and steepening of the market impact curve and a widening of the bid–ask spreads.

Monetary Liquidity and the Policymaker's Toolbox

Another form of liquidity feeds into the cycle of market and funding liquidity. Foucault, Pagano, and Roell [2013] pointed to the fact that market liquidity and funding liquidity are different notions which are accordingly affected by different policy actions: market liquidity by security market regulation and funding liquidity by banking regulation, specifically by the role of the central bank as lender of last resort. This brings us to a third kind of liquidity: the monetary dimension.

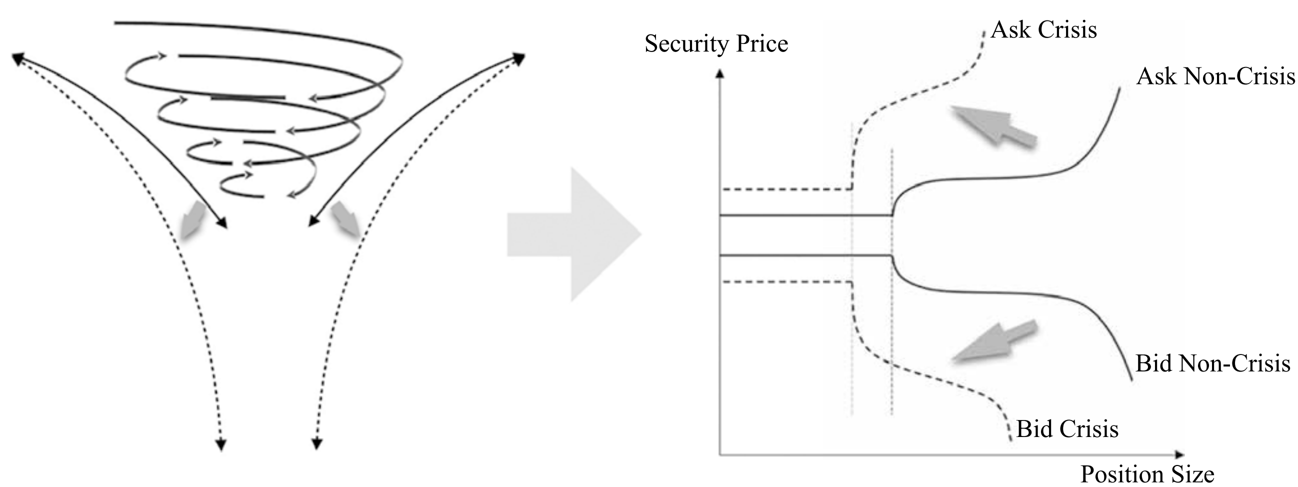
In terms of market liquidity, the most liquid asset is obviously cash, which by definition is universally accepted in exchange for goods at very stable terms (except in times of hyperinflation). Sorting assets by their liquidity, financial securities such as stocks and bonds come next at intermediate levels of market liquidity, whereas real assets sit at the opposite extreme. This explains why, in practice, liquidity is often identified with money itself (especially in macroeconomics), whether defined as the cash held by households, firms, and bank reserves (monetary base) or as broader monetary aggregates that also include bank deposits of various types (M1, M2, or M3). From that perspective, the discussion around contagion and flight to quality can be seen more generally as a polarization effect caused by a capital redistribution from the less liquid to the more liquid segments of the spectrum. Re-establishing market liquidity on the less liquid end thus can help rebalance the allocation of capital across markets.

The monetary notion of liquidity bears further relationship to the previous two types of liquidity: Expansion of the money supply by the central bank (e.g., via open market purchase of bonds, or *quantitative easing*) increases the supply of funds to banks and thus tends to increase funding liquidity, and with it market liquidity. By the same token, a monetary contraction can be expected to reduce both funding and market liquidity.

Of course, these relationships are neither mechanical nor stable over time. For example, banks and other financial intermediaries can generate different amounts

EXHIBIT 8

Worsening Conditions in Liquidity Crisis Widens Transaction Price Uncertainty Distributions



Note: As liquidity spirals become more severe, the market impact curve steepens and related transaction price uncertainty distributions widen.

of funding liquidity given the same level of money supply. Conversely, they may respond to an expansion of the monetary base by increasing their reserves with the central bank rather than by increasing their lending.

PRICE UNCERTAINTY DISTRIBUTIONS—A NEW WAY OF THINKING ABOUT LIQUIDITY

Having looked at the classical definitions of liquidity and how market microstructure naturally leads to approaching liquidity as an approximately square-root-shaped market impact model in equity markets, it is clear that, despite fundamental differences between limit order and dealer markets, the same principles can and should be extended to measure liquidity in OTC markets. The fact that, to date, market participants have typically relied on a wide range of proxies to measure liquidity in OTC bond markets comes down to the scarcity of data. There are two silver linings on the horizon regarding transparency and data availability:

1. Transparency initiatives similar to TRACE (such as MiFID II) are being rolled out across the globe and are being extended to further asset classes; and
2. Computational cost has fallen to a level that has made big data techniques available, allowing better use of existing financial data.

In hindsight, we expect this will mark the breakthrough point of a new paradigm as it will facilitate more accurate and consistent measurement of liquidity across asset classes, allowing the emergence of liquidity as a standalone risk factor. This is a vital step toward the integration of liquidity in enterprise risk management frameworks and regulatory reporting.

Frictions—Capturing the Complexity of Markets

There is one final obstacle to tackle and doing so will fully enfold the price uncertainty approach we suggest to capture liquidity in OTC markets. In addition to market microstructure and inventory risk, other frictions exist, adding further complexity to the liquidity picture and thus how to create an appropriate model to measure it.

The way in which securities are traded in reality is very different from the idealized picture of a frictionless and self-equilibrating market offered by the typical finance textbook. In the following we will see that this not only drives a wedge between value and price that can be attributed to liquidity, but also that this wedge can prove to be different for different market participants. Eventually, we suggest to think of liquidity as a distribution of transaction prices in a probability density space that reflects not only transaction volume and market conditions, but also the specific ability of a given trader/institution to overcome frictions. Altogether, these differences debunk the law of one price for all, establishing the need to account for price uncertainty as a reality in OTC markets.

Feldhütter [2012] studied the way in which the same bond can trade at different prices at approximately the same time, and how market conditions can have a significant influence on this phenomenon. Exhibit 9 is borrowed from this work and exemplifies the resulting price dispersion, which is further explored in the passages to follow. Vayanos and Wang [2012] took this thinking one step further and suggested that illiquidity can be viewed as a consequence of various forms of market frictions. Evidence across a large body of theoretical literature shows that even simple imperfections can break the clean properties of the idealized, perfect-market model and lead to rich and complex behavior.

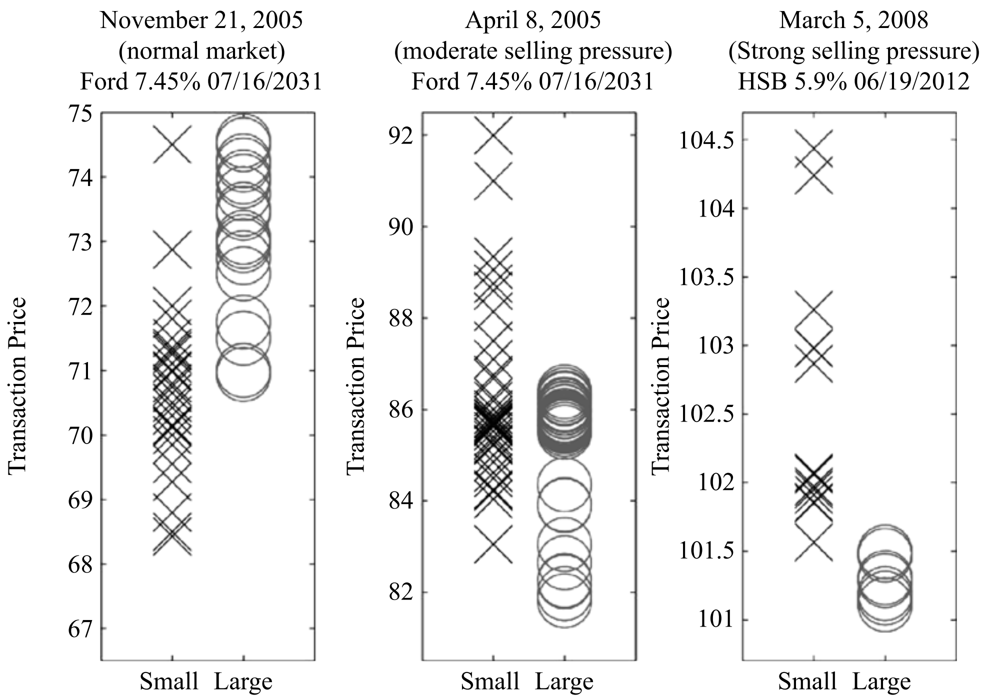
Frictions Shake the Efficient Market Hypothesis

Drawing explanations from Foucault, Pagano, and Roell [2013], the efficient market hypothesis (EMH) claims that security price changes are induced by the arrival of new information and should follow a random walk. The EMH is a useful benchmark model, but it fails to capture some important aspects of the intraday trading process. First, empirical studies have shown that intraday volatility is too great to be explained solely by news (French and Roll [1986], Roll [1988]). This suggests the trading process itself is a source of volatility. Second, the benchmark model fails to capture the simple fact that positive bid–ask spreads are the norm. Finally, in practice, intraday changes in prices are often negatively correlated (see, e.g., Stoll [2000] for empirical evidence).

Foucault, Pagano, and Roell [2013] showed how these different features of the intraday process can be captured if frictions are introduced, by relaxing the following assumptions:

EXHIBIT 9

Transaction Price Uncertainty—Bonds can Trade at Different Prices at Approximately the Same Time



Note: Small (below $100,000) and large trades in a normal market, under moderate selling pressure and under strong selling pressure, for a bond during a day
Source: Feldhuetter [2012].

- dealers are risk neutral and competitive
- investors do not have more information than dealers
- trading is cost-free

Instead, the models they present describe three kind of cost for liquidity suppliers:

- the cost of holding risky assets (inventory risk)
- the cost of trading with better informed investors (adverse selection costs)
- the real cost of processing orders (order-processing costs)

In addition, Duffie, Gârleanu, and Pedersen [2005] consider a search element: From the viewpoint of the perfect-market benchmark, the market is organized as a centralized exchange, whereas in more decentralized OTC markets, investors negotiate prices bilaterally with dealers. Consequently, and in contrast to the inventory risk and adverse selection schools of thought, in the model suggested by Duffie, Gârleanu, and Pedersen [2005], bid and ask prices are set in light of investors' outside options, which reflect both the accessibility of other market makers and investors' own abilities to find counterparties. Their research showed that the easier it is for investors to interact with each other directly, the lower the bid–ask spreads are found to be. The intuition behind this result is that more competition would drive down prices.

Duffie, Gârleanu, and Pedersen [2005] further suggested that if investors are more sophisticated (and consequently have better access to other investors or to market makers who do not have total bargaining power, for example), they receive a tighter bid–ask spread. This implication sets their theory of intermediation in stark contrast to information-based models (such as that of Glosten and Milgrom [1985]), in which more sophisticated (better informed) investors receive a wider bid–ask spread.

A testable implication of the search framework is that smaller investors, who typically are less informed and have fewer search options, should receive less favorable prices. More sophisticated investors, in turn, should receive better prices and see less dispersion in the prices they get. Evidence from the municipal bond market (e.g., the Securities and Exchange Commission [2004]) is consistent with these implications. The trading costs for municipal bonds are substantially higher than for equities, particularly high for retail-sized rather than institutional trades. The Securities and Exchange Commission's [2004] research further shows that prices for retail transactions are dispersed even though intraday fluctuations in the fundamental value of municipal bonds are minimal. By contrast, there is less price dispersion for large, institutional transactions.

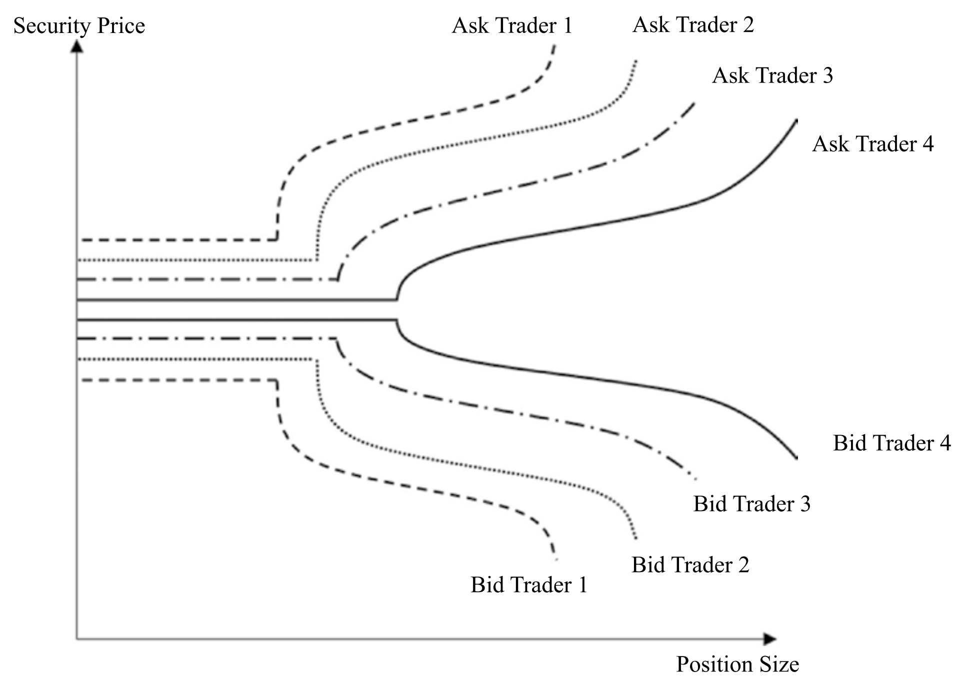
Interestingly, Duffie, Gârleanu, and Pedersen [2005] and Foucault, Pagano, and Roell [2013] presented comparable evidence obtained from independent studies and different markets. We therefore suggest formulating these findings more generally for OTC markets and beyond the search dimension, such that different levels of sophistication with regard to overcoming frictions can influence the distribution of probable transaction prices beyond transaction volume and market condition and, correspondingly, can explain different levels of prices for different market participants.

There Is No One-for-All-Market

Market microstructure and frictions are clearly the origins for (or at least strongly related to) liquidity and reveal the true extent of market complexities that needs to be accounted for when trying to capture the multidimensional beast. In light of the preceding information, it would make sense to consider that actual calibrations of market impact models may need to be adjusted to capture the individual market realities of a particular trader/institution. A practical way to do so would be to calibrate a general model to an individually obtained track record of transaction prices and position sizes.

The direct implications from this are profound: There is no such thing as a one-for-all market in OTC bond markets. Instead, the market a particular trader/institution faces and that market's properties—such as the price to be paid for liquidity—depend not only on the risk profile and the related valuation uncertainties of an asset being transacted, but also on associated market imperfections and a trader's/institution's ability to overcome them. Exhibit 10 shows how this leads to a range of possible market impact curves for different

Exhibit 10
Range of Market Impact Curves



Note: Transaction price uncertainty distributions stylizing the abilities of different traders to overcome frictions in OTC Markets.

traders/institutions (albeit in a highly stylized and exaggerated manner), which results in price dispersion. In the literature, this (or at least similar) thinking is reflected in the works of Cetin, Jarrow, and Protter [2004], Jarrow and Protter [2005], and Acerbi and Scandolo [2007]. Looking at this range of possibilities in light of previously established results from the sections on price-dispersion measures as well as market conditions, we suggest that this can be naturally captured in a transaction price uncertainty framework that is closely related to the concept, if not the nature of liquidity.

CAPTURING THE BEAST: TOWARD A NEW FRAMEWORK

A key finding emerging from the literature review presented in the previous sections is that a coherent, generally accepted approach to measuring liquidity is, to this day, completely unavailable. We believe that such a gap is in essence caused by lack of transaction data in fragmented markets or, in other words, insufficient transparency in the fixed income (OTC) markets.

A new framework to deal better with this root cause should have at its core the comprehensive integration of all available financial information. This strategy will require making use of modern data analysis and aggregation techniques, commonly known as artificial intelligence. Indeed, machine learning methods have become ubiquitous in providing interpretability for very large datasets as well as extracting desired information from extremely sparse data.

More specifically, a meaningful measure of liquidity should estimate the transaction price uncertainty distribution respective to the expected cost to liquidate a specific position size in a given time frame and market condition. This can be seen as a generalization of market impact models typically used in equity markets to a framework that captures the main complexities present in OTC markets and hence allows us to measure liquidity consistently across various asset classes. Moreover, given the inherent uncertainty of such a measure, a consistent mathematical framework needs to be used to quantify its degree of certainty. It is precisely here that the need for a machine learning approach is apparent in combination with the appropriate statistical/econometric methodology for the inference process.

The development of a methodology along the guidelines outlined will be the subject of a forthcoming paper.

ENDNOTE

The authors are grateful to Peter Chu and Peiyu Rang for their hard work and loyalty since the beginning of this long journey, Luca Spampinato for his support and wise man advice, Attilio Meucci for tough quantitative challenges as well as Vera Newhouse for being "Vera" and all her help in getting this published. Last but not least, we want to thank the entire LQA team for all the inspiring work and fun that as well transpired into this article together. Before all, thank you to our wives Antje and Alessandra for being patient with and believing in us.

REFERENCES

Acerbi, C., and G. Scandolo. "Liquidity Risk Theory and Coherent Measures of Risk." Working paper, Abaxbank and Universita di Firenze, 2007.

Aitken, M., and C. Comerton-Forde. "How Should Liquidity Be Measured?" *Pacific-Basin Finance Journal*, 11 (2003), pp. 45-59.

Almgren, R., "Optimal Execution with Nonlinear Impact Functions and Trading-Enhanced Risk." *Applied Mathematical Finance* (2003), pp. 1-18.

Almgren, R., C. Thum, E. Hauptmann, and H. Li. "Direct Estimation of Equity Market Impact." *Risk*, July 2005, pp. 57-62.

Amihud, Y. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets*, Vol. 5, No. 1 (2002), pp. 31-56.

Amihud, Y., and H. Mendelson. "Liquidity, Maturity, and the Yields on U.S. Treasury Securities." *Journal of Finance*, November/December 1991, pp. 1411-1425.

Amihud, Y., H. Mendelson, and L.H. Pedersen. *Market Liquidity: Asset Pricing, Risk, and Crises*. Cambridge: Cambridge University Press, November 2012.

Bagehot, W. "The Only Game in Town." *Financial Analysts Journal*, March/April 1971, pp. 12-14.

Bangia, A., F.X. Diebold, T. Schuermann, and J.D. Stroughair. "Modeling Liquidity Risk, with Implications for Traditional Market Risk Measurement and Management." In *Risk Management: The State of the Art*, edited by S. Figlewski and R. Levich, pp. 1-13. Amsterdam: Kluwer Academic Publishers, 2001.

Basel Committee. "Basel 3: The Liquidity Coverage Ratio and Liquidity Risk Monitoring Tools." January 2013, http://www.bis.org/publ/bcbs238.htm.

Benston, G.J., and R.L. Hagerman. "Determinants of Bid–Asked Spreads in the Over-the-Counter Market." *Journal of Financial Economics*, December 1974, pp. 353-364.

Black, F. "Fundamentals of Liquidity." June 1970, http://www.rasmusen.org/special/black/FundamentalsofLiquidity70.pdf.

Bouchaud, J.P., Y. Gefen, M. Potters, and M. Wyart. "Fluctuations and Response in Financial Markets: The Subtle Nature of 'Random' Price Changes." *Quantitative Finance* (2004), pp. 176-190.

Brunnermeier, M.K., and L.H. Pedersen. "Market Liquidity and Funding Liquidity." *Review of Financial Studies*, June 2009, pp. 2201-2238.

Bushman, R., A. Le, and F.P. Vasvari. "Implied Bond Liquidity." Working paper, 2010.

Cetin, U., R.A. Jarrow, and P. Protter. "Liquidity Risk and Arbitrage Pricing Theory." *Finance and Stochastics*, 8 (2004), pp. 311-341.

Chordia, T., R. Roll, and A. Subrahmanyam. "Commonality in Liquidity." *Journal of Financial Economics*, 56 (2000), pp. 3-28.

Dastidar, S., and B. Phelps. "Introducing LCS—Liquidity Cost Scores for U.S. Credit Bonds." Barclays Capital, October 2009.

Demsetz, H. "The Cost of Transacting." *Quarterly Journal of Economics*, February 1968, pp. 33-35.

Dick-Nielsen, J., P. Feldhütter, and D. Lando. "Corporate Bond Liquidity before and after the Onset of the Subprime Crisis." *Journal of Financial Economics*, 103 (2012), pp. 471-492.

Duffie, D., N. Gârleanu, and L.H. Pedersen. "Over-the-Counter Markets." *Econometrica*, November 2005, pp. 1815-1847.

Eisfeldt, A.L. "Endogenous Liquidity in Asset Markets." *Journal of Finance*, Vol. 59, No. 1 (2004), pp. 1-30.

Eisler, Z., J.-P. Bouchaud, and J. Kockelkoren. "The Price Impact of Order Book Events: Market Orders, Limit Orders and Cancellations." *Quantitative Finance*, Vol. 12, No. 9 (2012), pp. 1395-1419.

Engle, R, R. Ferstenberg, and J. Russell. "Measuring and Modeling Execution Cost and Risk." *The Journal of Portfolio Management*, Vol. 38, No. 2 (2012), pp. 14-28.

European Banking Authority. "On Defining Liquid Assets in the LCR under the Draft CRR." Discussion paper, February 2013, http://www.eba.europa.eu.

European Banking Authority Banking Stakeholder Group. "Response to EBA discussion paper 'On Defining Liquid Assets in the LCR under the Draft CRR.'" March 2013, http://eba.europa.eu.

European Savings Bank Group. "Response to EBA discussion paper 'On Defining Liquid Assets in the LCR under the Draft CRR.'" March 2013, http://eba.europa.eu.

Feldhütter, P. "The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures." *Review of Financial Studies*, Vol. 25, No. 4 (2012), pp. 1155-1206.

Ferraris, A. "Equity Market Impact Models." Deutsche Bank AG presentation, December 2008, http://dbquant.com/Presentations/Berlin200812.pdf.

Fleming, M.J., "Measuring Treasury Market Liquidity." *FRBNY Economic Policy Review*, September 2003, pp. 83-108.

Foucault, T., M. Pagano, and A. Roell. *Market Liquidity: Theory, Evidence, and Policy*. Oxford: Oxford University Press, 2013.

French, K.R., and R. Roll. "Stock Return Variances: The Arrival of Information and the Reaction of Traders." *Journal of Financial Economics*, 17 (1986) pp. 5-26.

Friewald, N, R. Jankowitsch, and M.G. Subrahmanyam. "Liquidity, Transparency and Disclosure in the Securitized Product Market." SSRN abstracts, August 2012, http://ssrn.com/abstract=2139310.

Gatheral, J. "No-Dynamic-Arbitrage and Market Impact." *Quantitative Finance*, Vol. 10, No. 7 (2010), pp. 749-759.

Gehr, A.K., and T.F. Martell, "Pricing Efficiency in the Secondary Market for Investment-Grade Corporate Bonds." *The Journal of Fixed Income*, Vol. 2, No. 3 (1992), pp. 24-38.

German Banking Industry Committee. "Response to EBA discussion paper 'On Defining Liquid Assets in the LCR under the Draft CRR.'" March 2013, http://eba.europa.eu.

Glosten, L. "Insider Trading, Liquidity and the Role of the Monopolist Specialist." *Journal of Business*, April 1989, pp. 211-235.

Glosten, L., and P. Milgrom. "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." *Journal of Financial Economics*, 14 (1985), pp. 71-100.

Grinold, R.C., and R.N. Kahn. *Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Controlling Risk*, 2nd ed. New York: McGraw-Hill, 1999.

Grossman, S.J., and M.H. Miller, "Liquidity and Market Structure." *Journal of Finance*, Vol. 43, No. 3 (1988), pp. 617-637.

Harris, L.E. *Liquidity, Trading Rules, and Electronic Trading Systems*. New York: New York University Salomon Center Monograph Series in Finance, 1990-4, 1990.

Houweling, P., A. Mentink, and T. Vorst. "Comparing Possible Proxies of Corporate Bond Liquidity." *Journal of Banking and Finance*, June 2005, pp. 1331-1358.

Huberman, G., and W. Stanzl, "Price Manipulation and Quasi-Arbitrage." *Econometrica*, July 2004, pp. 1247-1275.

Jankowitsch, R., H. Mösenbacher, and S. Pichler. "Measuring the Liquidity Impact on EMU Government Bond Prices." Working paper, Vienna University, CCEFM and National Bank of Austria, February 2002.

Jankowitsch, R., A. Nashikkar, and M. Subrahmanyam. "Price Dispersion in OTC Markets: A New Measure of Liquidity." *Journal of Banking and Finance*, 35 (2011), pp. 343-357.

Jarrow, R., and P. Protter. "Liquidity Risk and Risk Measure Computation." *Review of Futures Markets*, Vol. 11, No. 1 (2005), pp. 27-39.

Johnson, T.C. "Volume, Liquidity, and Liquidity Risk." *Journal of Financial Economics*, Vol. 87, No. 2 (2007), pp. 388-417.

Lee, C.M.C., and M.J. Ready. "Inferring Trade Direction from Intraday Data." *Journal of Finance*, June 1991, pp. 733-746.

McGinty, L. "Issue Size versus Liquidity in Credit." J.P. Morgan Fixed Income Research internal document, 2001.

Mehrling, P. *The New Lombard Street: How the Fed Became the Dealer of Last Resort*. Princeton, NJ: Princeton University Press, November 2010.

——. *Fischer Black and the Revolutionary Idea of Finance*. Hoboken, NJ: John Wiley and Sons, December 2011.

Perold, A.F., and R.S. Salomon Jr. "The Right Amount of Assets Under Management." *Financial Analysts Journal*, May–June 1991, pp. 31-39.

Petrella, G., and A. Resti. "Basel 3 and the Liquidity of Corporate and Government Bonds in Europe." *Bancaria*, March 2013, pp. 22-36.

Roll, R. "A Simple Implicit Measure of the Effective Bid–Ask Spread in an Efficient Market." *Journal of Finance*, September 1984, pp. 1127-1139.

——. "R-Squared." *Journal of Finance*, 43 (1988), pp. 541-566.

Sarig, O., and A. Warga. "Bond Price Data and Bond Market Liquidity." *Journal of Financial and Quantitative Analysis*, September 1989, pp. 367-378.

Schultz, P.H. "Corporate Bond Trading Costs: A Peek behind the Curtain." *Journal of Finance*, April 2001, pp. 677-698.

Securities and Exchange Commission. "Report on Transactions in Municipal Securities." Office of Economic Analysis, July 2004.

Stoll, H.R. "AFA Presidential Address: Friction." *Journal of Finance*, Vol. 55, No. 4 (2000), pp. 1479-1514.

Toth, B., Y. Lemperiere, C. Deremble, J. de Lataillade, J. Kockelkoren, and J. Bouchaud. "Anomalous Price Impact and the Critical Nature of Liquidity in Financial Markets." May 2011, http://arxiv.org/abs/1105.1694v1.

Vasvari, F.P. "Measuring Liquidity in the Bond Market." CARE/CEASA conference presentation, 2011, http://nd.edu/care-cob/April2011Conference/Vasvari.pdf.

Vayanos, D., and J. Wang. "Market Liquidity: Theory and Empirical Evidence." Financial Markets Group Discussion Paper No. 708, July 2012.

one **Point of View**

ETFs, Hedge Funds and Democracy

Research compiled by Michael Venuto, CIO and David Dziekanski, Portfolio Manager

This month ETFGI, a wholly independent research and consultancy firm founded Deborah Fuhr, has made headlines with their data showing that global ETP assets will soon surpass the assets held in hedge funds. The following was excerpted from their website:

"According to our analysis published on April 24th, assets in the global ETF/ETP industry reached a new record of US$2.926 trillion at the end of Q1 2015, while assets in the global hedge fund industry, according to a new report published by Hedge Fund Research (HFR), reached a record US$2.939 trillion. Assets in the ETF/ETP industry have been gaining on those invested in the hedge fund industry with the difference narrowing from US$230 billion at the end of 2013 to just US$13 billion at the end of Q1 2015."

It is important to note that this inflection point coincides with record assets under management for WisdomTree Investments, Inc. (WETF). Today, close to 60% of WisdomTree's assets are currency hedged products that were modeled off of established hedge fund trades. Perhaps the parity reached in the hedge fund assets to global ETP assets can be partially attributed to the role ETFs have played in democratizing exposures that have traditionally only been available to investors willing to pay a 2% management fee and 20% of their profits with 10-year lock ups.

What other hedge fund trades are now available through an ETF, and what else could be done in the future? Toroso recently took a deeper look into this emerging ETF category and here is what we found.

The Evolution of Hedge Fund Trades

First let's review the evolution. IndexIQ and their flagship IQ Hedge Multi-Strategy Tracker ETF (QAI) deserves credit as the pioneer in the hedge fund replication landscape. It took many years but we believe the ETF is now one of the preferred alternative ETFs for many wire-house platforms and has gathered about $1 billion in assets. The irony is that the returns of hedge funds as a whole and QAI are less than exciting for investors, annualizing at around 4.2% since inception, although with reduced volatility.

This lackluster performance, when compared to the six year bull-run we are experiencing in the market now, led to a different set of hedge fund like products we call the cherry pickers. Today there are six ETFs that seek exposure to the top ideas of hedge fund managers. The goal of these products is not to replicate returns but to capture the alpha. For the most part, we believe they have worked and have produced excess returns above traditional indexes. That said, the hedging aspect used to reduce volatility is absent from most of these products. AlphaClone Alternative Alpha ETF (ALFA) is the exception; the index includes a moving average calculation that allows the ETF to take a short position on the S&P 500.

ETF	Ticker
AlphaClone Alternative Alpha ETF	ALFA
Direxion iBillionaire Index ETF	IBLN
Global X Guru™ Index ETF	GURU
Global X Guru™ Activist ETF	ACTX
Global X Guru™ International ETF	GURI
Global X Guru™ Small Cap Index ETF	GURX

*Toroso Investments, LLC is a partially- owned affiliate of Global X Management Company.
** At the time of this writing Toroso clients had investments in ALFA, EMQQ, FMLP and GEUR.

The Currency Hedge

In the introduction we noted that today 60% of the WisdomTree assets are now currency hedge. This trade or exposure has long been a darling in the hedge fund community. WisdomTree has been rewarded for democratizing this exposure with assets and last year received the biggest compliment any ETF sponsor can achieve. iShares has copied them. In January 2014 iShares launched Currency Hedged MSCI EAFE ETF (HEFA). While this kind of competition may be flattering for WisdomTree, Toroso believes the more interesting news in the currency hedged space is the new comers like Gartman Gold/Euro ETF (GEUR) from Advisorshares. This ETF allows investors to buy gold exposure while shorting the Euro. Toroso expects to see more currency/commodity paired trades in future ETFs.

Accessing Publically Traded Hedge Funds through ETFs

Another interesting concept is to directly invest in publicly traded hedge funds through an ETF. Unfortunately this is not yet possible due to two indexing issues. Many publicly traded hedge funds have low floats due to high insider ownership, which makes them difficult to include in ETFs. The best example is Ichan Enterprises L. P. (IEP) - Carl Ichan owns close to 90% of the outstanding shares, which substantially diminishes the liquidity. The second issue is most publicly traded hedge funds use a partnership corporate structure that is excluded from most indexes because of the tax implications. So although there is not yet an ETF for this space there is an ETN that owns many of these publically traded hedge funds. Although investors would never know it from the name, the ETRACS Wells Fargo MLP Ex-Energy ETN (FMLP) provides investors access to private equity and hedge fund partnerships. Here are the top ten index constituents as of May 11, 2015:

Name	Ticker	%
Blackstone Group LP	BX	10.83
Carlyle Group LP	CG	10.71
Icahn Enterprises LP	IEP	9.89
KKR & Co LP	KKR	9.56
Apollo Global Management LLC	APO	9.44
Oaktree Capital Group LLC	OAK	8.95
Lazard Ltd	LAZ	8.03
Och-Ziff Capital Management LLC	OZM	6.88
Brookfield Property Partners LP	BPY	6.66
Ares Management LP	ARES	4.47

The Emerging Markets Opportunity

Another interesting hedge fund exposure is emerging markets. In general hedge funds have specialized in emerging markets to capitalize on growth and inefficiencies. An interesting subset, for which Tiger Global Management is a known investor, is the emerging market online consumer. Many hedge funds have been early investors in companies like JD.Com Inc. (JD) and Alibaba Group Holding Ltd (BABA). The Emerging Market Internet and E-commerce ETF (EMQQ) targets companies whose primary business is e-commerce or internet-related activities that generate most of their revenues in emerging market countries. Toroso sees this as a growth area because of the high return on equity and that it has less than 5% overlap to broad based emerging market ETFs like iShares MSCI Emerging Markets ETF (EEM).

The Future

So what is next? A common trade that many hedge funds are using today is too short in equal dollar amounts the leveraged long and leveraged inverse versions of an asset class they expect to be volatile. They are capitalizing on the well-documented phenomenon that in volatile environments the daily reset function of leveraged and inverse products causes erosion of principal. So for example, if hedge fund thinks financials will do well they could purchase Direxion Daily Financial 3X Bull (FAS), or if they think financials will do poorly they could purchase Direxion Daily Financial 3X Bear (FAZ). By shorting both in equal amounts a third opinion can be expressed: "financials will be volatile."

This trade has become very popular with hedge funds because it is more efficient than the traditional option straddles that are used to express volatility opinions. However, there are number of drawbacks to the trade. First the pair will lose money in a low volatility trending market. In addition, there are two structural issues; there can be high borrowing cost to short the ETFs and the trading and tax consequences of keeping the exposure balanced can be cumbersome. These two structural issues could be mitigated by placing and maintaining this pair's trade in an ETF structure. The scale of the ETF structure and the relationship sponsors have with liquidity providers should reduce the borrowing and transaction costs, and the rebalancing process with authorized participants should reduce the tax consequences. This would give ETF investors the ability to express volatility opinions just like hedge funds, but more efficiently.

Investment Flexibility Will Grow

Toroso is excited to watch the success of ETFs grow while democratizing exposure traditionally only available to hedge funds. We believe there is much more to come in this transparent and tax efficient structure.

Financial Services Newsletter

The Case for Fund Liquidity

By Kelly Westfall, CPA, CFA

Recent History

On December 9, 2015, something nearly unprecedented happened: The Third Avenue Focused Credit Fund (TFC) announced a halt on share transactions and made public its plan to liquidate. This was the largest mutual fund failure since the 2008 financial crises. The Fund's sponsor, Third Avenue Management LLC, was started by legendary investor Martin Whitman 29 years ago and had risen to over $26 billion at one point. As of year-end 2015, the asset management firm's assets under management had dropped to around $7 billion. The Fund itself, TFC, began its 2014 fiscal year with net assets nearing $3 billion. But by fiscal year end 2015, the Fund's assets had dropped to $1.4 billion having lost $500 million from operations and $940 million in net redemptions. $200 million was distributed to shareholders. By early December 2015, the Fund's assets had dipped further to about $800 million.

In a letter to shareholders dated December 9, 2015, Third Avenue's CEO, David Barse, wrote that "Investor requests for redemption…, in addition to the general reduction of liquidity in the fixed income markets, have made it impracticable for (TFC) going forward… to pay anticipated redemptions without resorting to sales at prices that would unfairly disadvantage the remaining shareholders." The letter goes on to explain the illiquid nature of the Fund's strategy and the need for a longer holding period to generate positive returns. Having spent a large part of my career analyzing and performing due diligence on investment funds and managers, I am familiar with the Fund's high-yield, distressed strategy. However, this is the first time I am aware of that the stated strategy of a fund, whether it be this one or any other, has been used as an excuse by an asset management firm's CEO to precipitate a freeze on mutual fund redemptions (which are required by regulatory mandate to be available within 7 days).

On December 14, 2015, Mr. Barse and Third Avenue Partners parted ways. According to *The Wall Street Journal*, Mr. Barse was told by his partners that "they were firing him, and he needed to vacate the building immediately, without stopping to collect his personal belongings." Mr. Barse was escorted from the building. The chaos to follow included emergency intervention by the SEC who reversed the Fund's plan to move the assets of TFC to a liquidation trust but allowed a temporary freeze on redemptions. Of course, more is yet to come.

As the credit markets braced for the potential string of failures, interested parties began to dissect the Fund and its management. It was shocking.

When Funds Close

Of course, it is not so unusual for pooled investment funds to dissolve; especially those with niche or concentrated, high risk strategies such as this one.

According to the *Alternative Investment Management Association (AIMA) Journal*, up to 10% of hedge funds trading each year close and liquidate. *The New Yorker* reported that over the five years beginning in 2010, approximately one-third of hedge funds closed. However, TFC is/was not a private hedge fund. But is rather an open-end, non-diversified, Securities and Exchange Commission (SEC) Registered Investment Company under the Investment Company Act of 1940; or, what is more commonly known as a “40 Act” mutual fund.

As a U.S. registered fund, the Fund’s portfolio is subject to rules and portfolio limits aimed at protecting retail investors. These protections differentiate mutual funds and exchange traded funds (ETFs) from hedge funds, the shares of which are only deemed suitable for sale to “Accredited” (high wealth, sophisticated) investors. Mutual fund shares on the other hand are generally seen as the bastion of safety, making up the foundation of 401(k) retirement accounts and, along with ETFs, are seen as sources of liquidity in private investor and institutional portfolios. In fact, the SEC’s www.investor.gov page lists liquidity as one of the four reasons people buy mutual funds.

“40 Act” funds in the U.S. are subject to regulatory mandates which generally include concentration limits on individual investments in securities and on investment in issuers of securities to 5% of the fund’s portfolio and 10% of the issuer, respectively. These limits do have some flexibility with regard to “non-diversified” funds such as TFC. Still, TFC was limited to concentration limits of 25% of securities and issuers with the exception of U.S. government securities.

There is also a 15% limit on illiquid assets for all U.S. registered investment funds which are described by the SEC as assets “which may not be sold or disposed of in the ordinary course of business within seven days.” Lastly, “40 Act” funds are required to price the portfolio daily and report the fund’s holdings at least quarterly. If followed, these limits and reporting requirements are intended to provide liquidity to meet redemptions in the ordinary course of business and protect against catastrophic liquidity events similar to the TFC closing.

The Rotation of “40 Act” Products

Yet, mutual funds do close and liquidate for a variety of reasons. In fact, hundreds of U.S. registered investment funds close every year; especially in light of the wave of new products coming to market in the past decade. In an effort to compete with low fee index tracking funds, issuers began launching a blitz of innovative “40 Act” products including “alternative” mutual funds and ETFs which seek to mimic hedge fund strategies. At the same time, issuers have been pressuring regulators to allow more and more esoteric strategies to come to market as registered funds. When asked about this, Vanguard’s Chairman and CEO, Bill McNabb, told CNBC’s Bob Pisani that he would welcome further regulatory hurdles and that “product proliferation has reached epic levels.” Vanguard credits its success to index tracking, passive strategies.

Although ETF investors have been less enticed to invest in “alternative” funds, the Division of Economic and Risk Analysis (DERA) reported in September 2015 that “alternative strategy (mutual) funds are growing faster than any other category.” Interestingly though, the 2014 EDHEC European ETF Survey noted that satisfaction among users of ETFs with hedge fund strategies is erratic and lower than other strategies. According to the survey, “the volatility in the satisfaction rates with ETFs based on the most illiquid asset classes may also be due to the suitability of ETFs for more liquid asset classes.” And as of year-end 2014, “alternative” mutual funds made up only 2.6% of the market. Either way, the result of this trend has been a surge of “40 Act” fund openings and closings.

Almost always, however, when a mutual fund closes it does so in an orderly fashion. The fund first closes to new investors; then current investors are given a period of time, generally several months, to redeem their shares. Fees are typically waived during this period.

So how is it possible that TFC closed so abruptly? The Fund's closure was exceptional in that it exemplified the exact series of events the SEC specifically aims to prevent; an inability to meet redemptions within seven days at the Fund's stated net asset value (NAV). In addition to highlighting, at least in this instance, the inability of regulators to ensure the liquidity safety net generally associated with registered investment funds, it also obviates the false level of security mutual fund and ETF investors have enjoyed.

Regulators Focus on Liquidity Rules and Monitoring

(In Response to Market Risks Created by Loosened Rules and Monitoring)

It turns out that although it is not common for "40 Act" funds to freeze or gate redemptions, concerns over liquidity and valuations have been building for some time. In fact, on September 22, 2015 the SEC issued a press release noting that that the Commission had "voted to propose a comprehensive package of rule reforms designed to enhance effective liquidity risk management by open-end funds, including mutual funds and exchange-traded funds (ETFs)." The press release quoted SEC Chair Mary Joe White as saying: "Promoting stronger liquidity risk management is essential to protecting the interests of the millions of Americans who invest in mutual funds and exchange-traded funds." At the time of the TFC closing, the Commission was in the process of receiving comments with the final rules to be published in January 2016. Then on January 13, Reuters reported that "U.S. securities regulators launched a review of potential liquidity risks posed by high-yield bond fund managers in the aftermath of the collapse of Third Avenue's junk bond fund in December." The article noted that regulators gave fund managers just 24 hours to turn over a slew of portfolio details related to pricing and liquidity.

Understanding Mutual Fund Liquidity and Valuation Risk

Fund analysis and due diligence is complex and multi-faceted. But in this case, we cannot escape focusing on two primary risk factors: fund liquidity and valuations.

Fund Liquidity

Understanding the true liquidity of an investment fund, either private or public, is not simply a matter of checking the fund's liquidity terms.

Underlying Liquidity and Investment Flows — According to EDHEC, "the liquidity of an ETF is determined by the liquidity of the underlying securities. If the underlying securities are illiquid, it is to be expected that the ETF will be illiquid." Additionally, the DERA report noted that alternative strategy funds face more volatile flows compared to more traditional funds noting that "during the period 1999 through 2014, the average standard deviation of monthly flows for alternative strategy funds was 13.6%, compared to only 5.8% for U.S. equity funds."

The volatility of flows to "alternative" funds, combined with the illiquid nature of the portfolio, materially increases the chance that a fund may not be able to maintain assets under management — a primary determinant of the success or failure of a registered fund.

Liquidity Gates — Mutual funds and ETFs do not have contractual liquidity gates. However, it is clear that this may not prevent them from putting one up. Almost all hedge funds, on the other hand, do contain at least one contractual discretionary gate which allows fund managers to freeze redemptions when the manager deems it to be “in the best interests” of its shareholders. Additionally, the majority of hedge funds contain other gates which can be triggered for a variety of reasons.

Contractual Liquidity Terms vs. Reality — As noted above, when a fund’s portfolio is illiquid, the fund is also illiquid. If the liquidity of a fund’s strategy and/or holdings is not consistent with the fund’s stated liquidity terms, the chance of a redemption freeze is heightened. In addition, when this situation exists, shareholders will experience both realized losses and missed opportunities if the fund experiences large redemptions regardless of whether or not there is a gate. By regulation, all investors who redeem from a mutual fund during the day transact at the fund’s end-of-day NAV. However, when the fund’s holdings are illiquid, the transactions associated with meeting those redemptions most likely occur on subsequent days. As a result, the costs of providing liquidity to investors are partially or entirely borne by the non-redeeming investors. In addition, as the “best” most liquid assets are sold to meet redemptions, current investors are left with the remaining less liquid assets.

When hedge funds face extreme redemptions, liquidity gates are enforced and the liquidity terms of the fund become irrelevant.

If a fund is event-driven or seeking distressed and high-yield debt opportunities (similar to TFC), the liquidity of the fund is most likely not daily or even monthly, regardless of the fund’s stated terms. Yes, the fund may maintain enough cash to handle a normal level of redemptions. But even that, from an investor point of view, is not desirable. The goal is to put money to work, not to enable the fund to grow more assets by proclaiming more frequent redemptions. Third Avenue’s web site described TFC as “A portfolio of high yield stressed and distressed securities with investments throughout the capital structure (high yield bonds, bank loans, convertible securities and/or preferreds) and across the credit spectrum (performing, stressed and/or special situations).” From what I can tell, this description is not a departure from the Fund’s actual strategy. However, the appropriateness of this strategy for a mutual fund structure is clearly questionable.

Illiquid Asset Classes — Distressed debt, private equity holdings, frontier and emerging market stocks and bonds, preferred equities and material holdings in small cap equities are other examples of strategies which are less liquid than, for example, investment grade bonds and large cap equities. So it is unrealistic to assume that a fund with large allocations to these less liquid asset classes would not be negatively affected by offering similar redemption terms as funds holding highly liquid assets; whether or not they close, put up a gate, or otherwise freeze redemptions.

Valuations

Pricing Illiquid Assets — Again, mutual funds are required to compute a net asset value daily and issue redemptions at share prices determined at the current day’s close. Illiquid assets are difficult to value and subject to modeling error as well as subjective pricing. Certain categories of fixed income securities, in particular, are rarely traded. Loans may not be traded at all. In the absence of actual transactions to support pricing, funds will determine pricing based on “dealer quotes” and models. Dealer quotes are prone to subjectivity in that the dealers may be hand-picked by the fund based on relationships or the attractiveness of their quotes. Models are opaque and are prone to modeling error as well as subjectivity.

Daily Math — A mutual fund manager who closed a credit fund during 2014 recently told me that one of the biggest reasons they shuttered their Fund was the difficulty of daily pricing. According to him, the process was error prone and pricing was impossible to calculate accurately on a daily basis — which again, is what regulations require. There were constant revisions and regulatory filings associated with the daily computations.

The facts as we know them seem to indicate that TFC's percent of illiquid assets, those assets which could not be liquidated at the quoted price within seven days, exceeded 15%. There is also a real possibility that TFC's valuations, for whatever reason, were not accurate.

So while the industry waits for regulators to respond, what should investors do? It is clear that there is an immediate need for an objective understanding of your investment fund's strategy and assets. Harry O'Mealia, the CEO of 1919 Investment Counsel, a $10 billion U.S. wealth management firm specializing in capital preservation and growth, advises that in this atmosphere you cannot rely on regulators to stay a step ahead of product marketing and that "unless you are reasonably sophisticated and are willing to put the time in to really understand what you own and why you own it, you should surround yourself with advisors whose judgment you trust."

How Can We Help?

Understanding Fund Strategy, Risk Profile and Underlying Assets

The Fund's Strategy and Holdings — The case is clear that it is no longer enough to rely on the protections provided by regulators when investing in mutual funds. Absent a review of the fund's strategy and underlying assets, the liquidity of the fund and the reliability of published valuations cannot be fully understood. Thus, the fund's allocation role in your portfolio may not be consistent with your goals and risk limits.

Fund Documents — Fund documents and regulatory filings should be scoured and summarized to ensure that the fund's key policies are in the best interests of investors; and that investor rights are sustained during times of market stresses and extreme redemptions.

Operations and Affiliations — In general, a fund's management, track record, and performance during market stresses as well as key elements of its operations, should be evaluated. It is true that TFC's strategy was designed as an extension of the strategy which has been honed at Third Avenue Capital Management, the Fund's sponsor, since its inception 29 years ago. But having never reviewed the operations of Third Avenue Capital Management, I cannot address the Firm's operational strengths or weaknesses which may or may not have contributed to the Fund's failure. But to properly analyze a fund, the fund sponsor should also be included in your due diligence review.

PKF O'Connor Davies Investment Strategy Consulting

Investment Strategy Consulting performs global investment and operational due diligence analysis. Our experience includes a wide variety of global funds, investment managers and investment products. Our proprietary due diligence criteria and risk ranking system objectively quantifies the inherent risks associated with complex investment managers and related structures, products and strategies. This analysis includes commentary on how these investment variables impact portfolio liquidity, asset allocation, operational risk, compliance and relative performance. We consider your investment goals and objectives first and maintain our objectivity and independent by setting our fees based upon value added services provided.

If looking unwind a fund, the PKF O'Connor Davies Financial Services Accounting Practice has the expertise and experience to help investors manage their investment wind down, redemption or liquidation process in an orderly manner, seeking to maximize your investment returns.

Contact

Kelly Westfall, CPA, CFA is the Director of Investment Strategy Consulting at O’Connor Davies LLP specializing in investment manager/fund due diligence, equity and alternative managers and products, and allocation recommendations as well as other types of specialized investment analysis. She has extensive experience in the United States and Europe conducting due diligence and consulting on portfolio allocations to investment managers, alternative investments, public funds and other complex investment products and advises on their use in the design and implementation of investment strategies. Her client base includes large institutional and high wealth investors with large, highly complex, investment portfolios such as multi-billion dollar foundations, pensions, family offices, endowments, and not-for-profit investors. Kelly also maintains oversight of the performance and risk reporting to several of the largest Foundations in the United States. For more information about our investment consulting services, contact Kelly at 646.449.6356 or kwestfall@pkfod.com.

About PKF O'Connor Davies

PKF O'Connor Davies Financial Services provides performance and risk reporting, and investment and consulting services, due diligence, valuation, attest (including audit, agreed upon procedures, surprise custody examinations and SOC reports), tax planning and compliance, complete fund administration and regulatory compliance (including Dodd-Frank, AIFMD, corporate and investment mandate compliance). We are CIMA-registered. Our administration unit was ranked 33rd largest global administrator by eVestment.net. Family Wealth Report shortlisted PKF O’Connor Davies Family Office for their 2016 Awards in accountancy advice, management consultancy, tax advice and philanthropy advice. Private Asset Management shortlisted PKF O’Connor Davies Family Office for best family office service provider, best reporting solution, best private client audit firm and best private client tax solution.

PKF O’Connor Davies, LLP is a full-service certified public accounting and advisory firm with a long history of serving clients both domestically and internationally. With roots tracing to 1891, 10 offices in New York, New Jersey, Connecticut and Maryland, and more than 600 professionals led by 100 partners, the Firm provides a complete range of accounting, auditing, tax and management advisory services. PKF O’Connor Davies is ranked number 29 on *INSIDE Public Accounting’s* 2015 “Top 100 Firms” list and is recognized as one of the “Top 10 Fastest-Growing Firms.” PKF O’Connor Davies is also recognized as a “Leader in Audit and Accounting” and is ranked among the “Top Firms in the Mid-Atlantic,” by *Accounting Today.* In 2016, PKF O'Connor Davies was named one of the 50 best accounting employers to work for in North America, by *Vault*. The Firm is the 11th largest accounting firm in the New York Metropolitan area, according to *Crain’s New York Business*.

PKF O’Connor Davies is the lead North American representative of the international association of PKF member firms. PKF International is a network of legally independent member firms providing accounting and business advisory services in 440 locations in 150 countries around the world.

Tuesday, February 2, 2016

Reprint

New-to-Market - This blog series highlights ETFs that have recently gone public and reflect those strategies currently most in demand by investors. While ETFs are not eligible for ETFG Risk Ratings until traded for 3 months and ETFG Reward Ratings for 12 months, our goal is to highlight the most cutting-edge investment strategies that have recently embraced the ETF structure – we hope you enjoy this special series of posts.

For the latest edition of the ETFG New-to-Market series, we're exploring the first actively managed utility ETF to hit the market, the Reaves Utilities ETF (UTES), built around the promise of pure sector exposure with all the liquidity and tax advantages of an ETF but with the promises of active management so far only found with mutual funds. So stick around as we pull a 180 from our usual fare of smart beta strategies and turn our sights to UTES.

In our last review, we joked that thanks to the rise of smart beta funds you could generally learn all you needed to know about a new ETF just by studying its name, which is why we normally start by focusing on underlying benchmarks and how they're constructed but that approach makes deconstructing UTES challenging because it doesn't actually have one! Sub-advised by Reaves Asset Management, a boutique research firm that was founded in the golden era of equity research (1961 to be precise) and focusing on energy and utility stocks, the firm employs a bottoms-up approach with no reference benchmark or trade schedule. Instead, they outline an investment philosophy that would be easily recognizable to any disciple of Benjamin Graham or Warren Buffet with a focus on searching out opportunities among well-capitalized names with strong balance sheets and a history of stable and growing earnings along with rising dividends. And how do they find these opportunities? While they employ a variety of quantitative processes, ultimately it involves doing their own leg work through management meetings and field research which to many of our readers who focus on data mining and machine learning may sound unique.

And while you think you know what constitutes a "utility", Reaves goes the extra mile to define their universe as companies either designated as utilities or those that derive at least 50% of their revenue, gross income or profits from the generation/distribution of gas, electricity or water which excludes the telecom and energy names that make up a large percentage of the average "utility fund." Why should that be important to you? Because the statistics for the average utility fund show that typically, around 74% of its allocation is actually in utility stocks with another 11% in telecoms and 10% in energy names. Now 74% is way more utility exposure than you'll find in any index fund and while sound in theory, telecoms and utilities have had a relatively low correlation to each other in the last decade with the net result being actively managed mutual funds underperforming "less diversified" passive utility index funds thanks to persistently weak telecom stocks.

As the only actively managed utility ETF, it might be fairer to compare UTES with its mutual fund brethren (and we'll get to that later) but advisers willing to consider investing in the strategy should know how it stacks up against the rest of space, especially the ubiquitous Utilities Select Sector SPDR (XLU.) And to be fair, those harried advisers who only have time to compare the two might wonder what exactly the hubbub is all about, especially with an almost 80 bps difference in fees. The 30,000 foot overview shows that both funds are highly concentrated and 100% invested in pure U.S. utilities although the management team at UTES retains the right to invest in ADRs or even to temporarily hold large amounts of cash (up to 100% of the fund) if they feel conditions warrant a defensive posture. In fact, a quick glance might seem to indicate that the only noticeable difference being a slightly lower average market cap for UTES that also helps generate a portfolio with less of the deep value feel that either XLU or the S&P 1500 Utilities index exudes. But once you get beyond the summary and start comparing the names, you'll find UTES to be a remarkably different portfolio that so far has held its own in 2016.

The first question any advisor will ask is just how different can the portfolio of UTES be from any index fund in such a small sector? The problems of concentrated portfolios with overlapping names are going to be difficult to avoid in any regulated market; the S&P 500 Utilities Index has a mere 29 stocks that make up just 3% of the index while the much broader S&P 1500 Utilities Index has just 59 for a whopping 3.3% of that much broader index. So how much overlap are we talking about? 16 of the 21 names that currently make up UTES are also included in XLU and in terms of percentage of the assets those 15 common holdings make up slightly more than 82% of UTES. But active management doesn't mean you can't hold the same names as your indexed competitors, you just have to be smart in how you use them and so far, the managers of UTES have lived up to the challenge. There are significant weighting differences between the two funds with only 2 of those 16 common holdings at UTES having an allocation within 100 bps of the index with significant underweights to major names like Southern Holdings while Duke Energy is completely missing from UTES. So what kind of performance differential can you expect with only 21 stocks and 16 of those in common with the much larger XLU? More than you would expect in such a short period.

While we're just one month into 2016, UTES has managed to hold its own against XLU with a 5% return for the month compared to 4.94% for XLU and more anemic 1.75% for the average utility mutual fund with among the biggest returners in that pool of common holdings being NiSource Energy, up 7.69% and which carries a nearly three times greater allocation at UTES than XLU. Cautious investors will note that NiSource is a distinctly midcap name although the management team at UTES also overweighted several large-cap names that are common holdings in the utilities space like Dominion Resources and NextEra Energy. So then why is UTES just holding its own with XLU? It certainly isn't due to poor security selection in the portion of the portfolio invested in names not held by XLU where Friday's surge made sure that none closed the month in the red. UTES also managed to avoid holding some of the worst performers in XLU's portfolio like Centerpoint Energy and the now notorious NRG Energy, whose 8.26% loss in January eroded nearly 20% of the gain from XLU's strongest single name not held by UTES, Consolidated Edison, even though NRG is just a .58% position!

In fact, when we started our comparison of the two funds at the start of last week, UTES was solidly outperforming XLU and it's only been in the last few days that the larger index fund has caught up with its new rival largely thanks to those weak performers like Centerpoint and NRG. Saying that the utilities sector has been gaining momentum against the broader equity market in 2016 is an understatement; from January 4th to the 19th XLU gained over 1.8% while the S&P 500 lost almost 8%. That sort of extreme outperformance wasn't likely to last, so of course from the 20th through the 26th the market managed to recover 1.19% while XLU lost ground (.75% to be exact), but it was during that time that UTES and its management team really managed to shine, losing only a mere .1%. But as volatility waned and investors returned to the markets in the second half of the week, they've been seeking out indexed products like XLU with a vengeance and that's helped some of the sector's worst performers like NRG and Centerpoint recover almost half of their losses in January. Putting it another way, a focus on higher quality names with strong earnings growth has been what has held UTES back.

We agree that one month does not a year make, not to mention that comparing an active and passive fund during a period of high volatility might make for an unfair comparison, so consider the performance of UTES and that of the largest active (and top-ranked) mutual fund in the Utilities category, Franklin Utilities (FKUTX). Franklin Utilities is managed by John Kohil whose fund carries four stars and a "Gold" ranking by absolutely dominating the space over the last decade with performance in the top decile in the three, five and ten year periods and often with significantly lower volatility than other funds in the space. So far the story in 2016 has stayed the same with a 4.02% return compared to the category's 1.75% gain and the secret of Franklin's success is that they have avoided most of the telecom and energy names that have held back other funds in that space with FKUTX currently holding 93% of its portfolio in U.S. utility names with just over 5.6% in energy stocks including Williams Companies. Compare that with the performance of MFS Utilities (MMUFX) with just 64% in utilities stocks and nearly 15% in energy stocks! In fact, only 68% of the overall portfolio is in domestic names, all of which helps explain why the fund is down 1.24% in 2016 and over 15.9% in the last year compared to a loss of 9.95% for the category.

So if that kind of performance spread between active mutual fund managers makes you queasy, or you just prefer to daily liquidity and tax advantages of an ETF, then the careful advisor is only left with one major decision; to benchmark or not to benchmark and for many the question will be decided over fee's. At 16 bps, XLU is one of the lowest priced ETF choices available and as a well-established fund has much greater liquidity than UTES, which has only been trading since last September and at 95 bps is the most expensive exchange traded option for clients. In a world of lowered expected returns, 79 bps isn't an inconsequential number but perhaps the better question for advisors to ask themselves is what kind of defensive equity exposure their clients were seeking. If they're trend followers and comfortable chasing momentum (and timing their entry and exit points) then XLU might be the choice but for those looking for a "buy-it and forget-it fund" to offer the right amount of upside potential and downside protection, it might be worth adding UTES to your portfolio.

Thank you for reading ETF Global Perspectives!

Assumptions, opinions and estimates constitute our judgment as of the date of this material and are subject to change without notice. ETF Global LLC ("ETFG") and its affiliates and any third-party providers, as well as their directors, officers, shareholders, employees or agents (collectively ETFG Parties) do not guarantee the accuracy, completeness, adequacy or timeliness of any information, including ratings and rankings and are not responsible for errors and omissions or for the results obtained from the use of such information and ETFG Parties shall have no liability for any errors, omissions, or interruptions therein, regardless of the cause, or for the results obtained from the use of such information. ETFG PARTIES DISCLAIM ANY AND ALL EXPRESS OR IMPLIED WARRANTIES, INCLUDING, BUT NOT LIMITED TO ANY WARRANTIES OF MERCHANTABILITY, SUITABILITY OR FITNESS FOR A PARTICULAR PURPOSE OR USE. In no event shall ETFG Parties be liable to any party for any direct, indirect, incidental, exemplary, compensatory, punitive, special or consequential damages, costs, expenses, legal fees, or losses (including, without limitation, lost income or lost profits and opportunity costs) in connection with any use of the information contained in this document even if advised of the possibility of such damages.

ETFG ratings and rankings are statements of opinion as of the date they are expressed and not statements of fact or recommendations to purchase, hold, or sell any securities or to make any investment decisions. ETFG ratings and rankings should not be relied on when making any investment or other business decision. ETFG's opinions and analyses do not address the suitability of any security. ETFG does not act as a fiduciary or an investment advisor. While ETFG has obtained information from sources they believe to be reliable, ETFG does not perform an audit or undertake any duty of due diligence or independent verification of any information it receives.

This material is not intended as an offer or solicitation for the purchase or sale of any security or other financial instrument. Securities, financial instruments or strategies mentioned herein may not be suitable for all investors. Any opinions expressed herein are given in good faith, are subject to change without notice, and are only correct as of the stated date of their issue. Prices, values, or income from any securities or investments mentioned in this report may fall against the interests of the investor and the investor may get back less than the amount invested. Where an investment is described as being likely to yield income, please note that the amount of income that the investor will receive from such an investment may fluctuate. Where an investment or security is denominated in a different currency to the investor's currency of reference, changes in rates of exchange may have an adverse effect on the value, price or income of or from that investment to the investor.