JOIM
www.joim.com

JOURNAL OF INVESTMENT MANAGEMENT, Vol. 13, No. 4, (2015), pp. 33–56
© JOIM 2015

IS U.S. INSIDER TRADING STILL RELEVANT? A QUANTITATIVE PORTFOLIO APPROACH

Carr Bettis[a,*], *John B. Guerard*[b] *and Daniel McAuley*[c]

For 40 years academic literature has reported statistically significant excess returns to selected insiders trading in their firms' shares, and similar evidence for outsiders who selectively mimic insider trading decisions spans three decades. However, constructing tradable signals leveraging insider trading data is challenging due to the irregular frequency of trades. We report that carefully constructed insider trading signals continue to produce statistically significant excess returns in US equity markets. We combine an insider factor with a non-insider stock selection model that is itself statistically significant and report economically meaningful incremental returns. The combined model is robust to different portfolio optimization techniques.

Academicians and practitioners often argue about the degree to which markets are efficient. The strong form of the Efficient Markets Hypothesis (EMH) holds, of course, that all information is embedded in stock prices. Academicians have cited the profitability of insider trading[1] and mutual fund performance as empirical evidence in conflict with the strong form of EMH. Indeed, there is a very large literature spanning over 40 years reporting statistically significant excess returns to United States legal insider trading. However, insiders also trade for reasons that are unrelated to private information, such as diversification (Bettis *et al.*, 2005), liquidity, taxes, and even to affect public perception of their firm (window dressing) (Jin and Kothari, 2005, 2008). In short, merely mimicking most of the transactions of insiders will not on average result in excess returns for portfolio managers over the long term. For example, the simple monthly insider trading metrics of Seyhun (1986) and Rozeff and Zaman (1988) applied to the largest 5,000 US securities by market cap (reconstituted each year) for the sample period 1998–2011 each produce statistically insignificant negative information coefficients of −0.002. Furthermore, even when advanced techniques are used to sort through

[a]Arizona State University, USA.
[b]McKinley Capital Management, USA.
[c]Verus Analytics, USA.
*Corresponding author: E-mail: carr@asu.edu.

Not for Distribution

the noisiness of insider trades, one is left with signals that are irregular, often infrequent, and distributed non-normally, making them impractical to use in isolation to build well-diversified portfolios. We construct a sophisticated Insider Trading Model (ITM), which generates significant excess returns on average, but nonetheless has these usual attributes. Our goal is not just to show that insider trading signals deliver information value but to demonstrate that this signal is valuable for investment management purposes. To this end, we combine it with a multifactor model and run portfolio optimization processes to demonstrate its incremental value to quantitative portfolios.

Specifically, we first construct ITM and linearly combine it with an Earnings Quality Model (EQM, see Appendix B) in order to leverage the proven relationship between these two disciplines and improve the distributional properties of the final legal insider trading (LIT) factor. While we demonstrate that LIT itself can be used to create portfolios with statistically significant excess returns, we take the next step to linearly combine LIT with the United States Expected Return (USER) model of Guerard *et al.* (2012), a regression-weighted multifactor stock selection model that is itself statistically significant. It incorporates fundamental data, such as earnings, book value, cash flow, and sales, as well as relative variables capturing how the fundamental data move in relation to their 5-year averages. The underlying fundamental and relative variables are combined with price momentum and an analysts' forecast variable as input to a regression-based model to identify the determinants of stock returns.

Using the linear combination of the buy and sell recommendations of USER and LIT we create mean variance-based portfolios. These portfolios generate excess returns above transactions costs and provide statistically significant asset selection. Specifically, the addition of LIT to USER enhances returns approximately 151 basis points annually, on average, over the 1997–2011 period and increases the Sharpe Ratios by up to 0.17 and information ratios by up to 0.25.

We follow with a brief discussion of the insider trading literature in the U.S. We provide a detailed description of ITM and place it in the context of EQM and the USER model. We end by presenting results for a variety of portfolio formation techniques.

1 Insider trading and future returns

Since the 1960s, research has frequently shown that insiders at U.S. companies can trade profitably on inside information (Lorie and Niederhoffer, 1968; Aboody and Kasznik, 2001; Cheng and Lo, 2006; Wu and Zhu, 2011). A number of studies also provide evidence that outsiders (i.e., investors who have no relationship with the firm) are able to earn excess returns by selectively observing the trades of corporate insiders (referred to as the outsider profit anomaly, for short) (Rozeff and Zaman, 1988; Giamouridis *et al.*, 2008). In this context, Givoly and Palmon (1985), Allen and Ramanan (1990), and Brochet (2010) suggest that the excess returns earned by outsiders are a function of the stock market reaction to the trades of the insiders as they become publicly available. In contrast, others speculate that the excess returns earned by outsiders are related to changes in fundamental company information that were first signaled by the trading actions of corporate insiders (Park *et al.*, 1995; Bettis *et al.*, 1997; Beneish and Vargus, 2002; Lakonishok and Lee, 2001; Huddart *et al.*, 2003; Huddart *et al.*, 2007; Piotroski and Roulstone, 2004; Cohen *et al.*, 2010).

Not for Distribution

While it is illegal for an insider to trade based on material nonpublic information, corporate insiders, especially those at the top of the executive hierarchy, invariably possess private information about their company and frequently use this information in trading their firms' securities (Moss and Kohers, 1990; Seyhun, 1992; Bettis and Coles, 1997; Jeng *et al.*, 2003; Piotroski and Roulstone, 2005). Insider transactions are legal if they are not based on specific and material private information pertaining to firm value, such as knowledge of surprising earnings or obtaining a very profitable contract. That is, insider trades are legal if they are based solely on intimate knowledge of the firm and its operating environment.

A number of studies document that insiders appear to adhere to U.S. securities regulations prohibiting trades around specific corporate events and announcements. Specifically, these studies find that insider trading activity is curtailed around significant informational events, such as earnings announcements (Garfinkel, 1997; Allen and Ramanan, 1990), bankruptcies (Loderer and Sheehan, 1989; Gosnell *et al.*,1992), dividend announcements (John and Lang, 2012), earnings forecasts (Penman, 1982, 1985), and securities issues (Karpoff and Lee, 1991). Indeed, insiders do trade for reasons that are unrelated to private information such as diversification (Bettis *et al.*, 2005), liquidity, taxes, and even public perception of their firm (window dressing) (Jin and Kothari, 2005, 2008). Unsurprisingly, no abnormal performance is seen after sales related to these types of events. That said, under specific conditions investors who intelligently parse through the noisiness of insider transaction data can earn abnormal returns over various holding horizons up to 12 months after analysis of the related insider transactions (Bettis *et al.*, 1997; Elliot *et al.*, 1984; Finnerty, 1976; Givoly and Palmon, 1985; Jaffe, 1974; Lakonishok and Lee, 2001; Pratt and Devere, 1970; Seyhun, 1986, 1992; Jagolinzer, 2009; Cohen *et al.*, 2010).

The quantitative analysis of insider transactions also necessitates an awareness of the changing regulatory landscape governing insider transactions and disclosures. Two examples of more recent changes include a 2-day reporting rule[2] and the adoption of and use of 10b5-1 trading plans. In short, we contend that evaluating the plethora of data (over 1 million transactions per year, on average) to find reliable, meaningful and investable trading signals is possible, although they require a scientific approach that takes into account the changing regulatory landscape.

The well-documented low information content of U.S. insider trading data in aggregate, combined with an evolving regulatory environment and shifting insider behavior, makes the extraction of meaningful signals from U.S. insider data particularly challenging. In the context of a multifactor quantitative portfolio containing additional, potentially correlated, information sources and which covers a large universe of securities, the construction of a robust and powerful insider trading-based factor is exceptionally challenging. Company-level insider sentiment variables form early literature, such as Seyhun (1992) and Rozeff and Zaman (1988), while predictive during in-sample periods, no longer correlate with future raw or excess share price performance. Additionally, we show that simple, univariate approaches to capturing insider sentiment do not provide adequate security universe coverage or statistically significant predictive power in the context of other explanatory factors. These challenges necessitate the inclusion of additional data sources, such as earnings quality variables, and relatively advanced statistical modeling techniques, such as principal component analysis, in a quantitative insider trading model. A model of such construction is detailed in the following section.

Not for Distribution

2 U.S. insider trading data and modeling

We utilize Thomson Reuters' U.S. Insider Trading data for our analysis. The data are constructed from Form 3, 4 and 5 data which are cleansed algorithmically and cross referenced with selected proxy data for named executive officers to ensure data integrity. Available data include the number and value of the shares traded, the type of the trade (buy, sell, exercise, or other types of transaction), individual holdings, position within the firm, and transaction and publicly available/reporting dates.

We account for the disparity between the volume of buying and selling by insiders in firms of different sizes. Because most U.S. executives generally receive a significant percentage of their compensation in equity and equity-related instruments, they sell more shares than they buy (Givoly and Palmon, 1985), especially in larger firms. Given that it is a rational decision for most undiversified insiders to sell shares (Carpenter and Remmers, 1998; Bettis *et al.*, 2005), we find that signals generated from selling activity are typically noisier than those using insider purchases. Purchasing company shares presents much lower litigation risk to an insider than selling shares (Huddart *et al.*, 2007). In short, insiders are more likely to buy if they possess positive information than they are to sell with negative information.

Finally, because we believe that most insider trades are not information based, we evaluate trades individually in order to isolate useful signals from the cacophony of trading occurring within a firm.

ITM utilizes the following variables:

Trade volume—Generally, higher trading volumes are associated with a greater probability of earning excess returns (Seyhun, 1998; Bettis *et al.*, 1997).

Trade value—Generally, higher valued trades are correlated with the information content of trades (Jenter, 2004; Atkas *et al.*, 2008).

Holdings ratio—The ratio of shares traded to holdings places current purchasing and selling into context by examining the impact of the transaction (increase or decrease) on the equity exposure of an individual. Generally, larger percentage increases or decreases in holdings are associated with a greater probability of indicating information-based sentiment (Jenter, 2004; Brochet, 2010).

Insider role—In general, higher position roles are associated with a greater probability of excess returns (Seyhun, 1986, 1992; Lin and Howe, 1990; Bettis *et al.*, 1997; Cheng and Lo, 2006; Fidrmuc *et al.*, 2006; Giamouridis *et al.*, 2008). However, Huddart and Lang (2003) suggest that the aggregate behavior of lower-level executives may have greater predictive power due to the reduced regulatory scrutiny of their transactions. This effect is counteracted by the decreasing level of inside information held by executives as one moves lower in the corporate hierarchy (Jeng *et al.*, 2003).

Consensus—Evaluates the level of purchasing and selling over the past 30 days, both in terms of shares traded and number of individuals involved. For example, if a greater number of insiders within a given firm have been buying than have been selling over the previous 30 day period this would be considered a positive sign. In addition, if the volume of the buying activity is also greater than that of the any selling activity we take this as a positive indicator, especially given that this occurrence is abnormal since selling transactions far outnumber purchases overall (Rozeff and Zaman, 1988; Seyhun, 1988, 1998; Lakonishok and Lee, 2001).

Not for Distribution

Momentum—Insiders are generally contrarian investors and tend to purchase shares of value firms that have unde rperformed historically (Rozeff and Zaman, 1988; Piotroski and Roulstone, 2004). They also trade more frequently in small firms, which have higher returns on average than larger companies (Lakonishok and Lee, 2001). We capture the direction and degree to which the shares an insider trades have appreciated or depreciated, and scale by the volatility of this share price movement. The model uses the t-statistic of a trend line fitted to the previous 260 trading days' prices. A minimum of 131 prices are required to calculate a reliable momentum value (Giamouridis *et al.*, 2008).

Trade ratio—While absolute measures of trade size capture significant information, the context of an individual's expected trading volume is also important. By analyzing the past buying and selling behavior of an individual an expected trade size is established. Deviations from this norm are captured in a simple ratio which indicates when an insider is buying or selling abnormally large amounts of company stock. We calculate the ratio of total shares traded to the expected trade size based on historical data.

Blackout flag—Trades made during corporate blackout periods, typically around earnings announcements, are theorized to provide less predictive power than those made during allowed trading windows. Given the increased risk to an insider for trading during one of these periods, less opportunistic behavior is observed. The model flags any filing where at least one trade of the same transaction code on the filing occurs during a blackout period. The blackout period is defined as 30 days before to 2 days after a company's earnings announcement (Bettis *et al.*, 2000).

Proven flag—The Thomson Reuters Proven Insider$^{\mathrm{TM}}$ indicator tabulates all insider historical trades (separately for purchases and sales) and calculates the absolute value of the t-statistic of the returns earned. All insiders are rank ordered by purchase and sale transactions providing a ranking for insiders who consistently earned excess returns from their trades in the past. We use the proven flag to identify potentially more prescient current trades.

Direct—Form 4 filers can be classified as "direct" or "indirect", depending on their relationship with the firm. If a Form 4 filing contains any trading whatsoever that is marked as direct then that whole trade is flagged as direct, otherwise it is flagged as indirect.

Option-related selling—We generally exclude trades where insiders exercise stock options and then immediately divest the underlying shares. Generally, these trades are noisier signals than if shares are sold outright.

10b5-1 Trading plans—Trading under correctly structured 10b5-1 plans is explicitly sanctioned. These plans can be terminated or initiated at the discretion of the executive (Henderson *et al.*, 2010). Research shows that insiders make above-market profits (by avoiding losses) using 10b5-1 plans but do not appear to arbitrarily or continually create such plans (Jagolinzer, 2009). In addition, 10b5-1 plans have a significant negative effect on the liquidity of a firm's shares, and therefore the firm's cost of capital (Robbins, 2008). We flag all sales made pursuant to 10b5-1 trading plans.

Size—Firm size is correlated with a number of factors that influence the expected information content of trades made by insiders. For example, larger firms tend to have greater analyst following and therefore are less likely to have material information surprises (Piotroski and Roulstone, 2004). We scale the market cap of the firm on the date of the trade by the price level of the S&P

Not for Distribution

500 Index on the same day in order to control for changes in the value of the aggregate U.S. equity market across time.

Sector—Sector alone has explanatory power in the context of insider trading modeling. Firms in sectors such as technology and healthcare tend to have higher stock price volatility and higher levels of incentive-based pay, thereby increasing the expected information content of informed trades made by company insiders. A set of sector indicators as interaction terms allows sector-specific coefficients for model variables. Standard and Poors' point-in-time Global Industry Classification (GIC) codes are used to identify a firm's sector.

Value—Insiders tend to be value investors, regardless of the information content of their trades (Rozeff and Zaman, 1988). In order to control for this effect, the model includes the market-to-book ratio of the firm.

Excess returns—Given the company-specific nature of inside information, our dependent variable must capture the idiosyncratic aspects of a company's share price performance. We calculate a firm's excess return compared to a portfolio of its size and sector peers. Specifically, the model defines excess performance as the firm's stock price return in excess of the average return of a basket of peer companies from a universe of the 5,000 largest U.S. firms by market capitalization, rebalanced each year. These comparable firms are from the same GIC sector and the same market cap size group defined by the following criteria each year end: large-cap stocks are the largest 400 U.S.-traded stocks ranked by market cap; mid-cap stocks are the next largest 500 stocks by market cap; small- and micro-cap stocks are the next 2,100 and 2,000 companies, respectively. The peer groups are created on the date that a given filing is made available in Thomson Reuters' Insider Trading Database.

ITM utilizes a 5-year rolling in-sample implemented by re-estimating model parameters at the end of each calendar year. The data used in these estimations consists of all transactions from the previous five calendar years. The coefficients calculated are used to predict excess returns for all filings over the next 12 months. For example, all the filings occurring in 2010 are scored based on coefficients which are calculated at the end of 2009 from data coming from the period 2005 to 2009, inclusive. This approach ensures that no ex-post data are used in the estimation of scores and preclude any look-ahead bias in the prediction process.

In order to capture the effects of certain variables that are conditional on other components and controls, we employ a second-order variable construction process. This methodology introduces statistical issues with regard to multicollinearity. To overcome these limitations and maintain robustness we use Principal Component Analysis (PCA) to create a smaller set of variables that retain the majority of the information contained in the original combined variable pool. Because insiders from the various company size and value groups behave differently, the number of filtered component variables may vary for the different year, transaction code, size, and market-to-book regressions.

Future excess stock price returns are then regressed on this reduced set of principal components in a stepwise fashion. The result is a predicted excess return for a stock every time there is a qualified filing by an insider in the company. To convert these predicted returns into scores we form buckets based on ranking returns from the in-sample (previous 5-year rolling period) and use cut-offs which are applied to the out-sample period (the following calendar year).

This modeling process, from variable combination to transaction scoring, is run separately for

Not for Distribution

buys and sells. These component models are further broken down by both size and market cap categories. Pooling data by size and value yields robust coefficients that are more meaningful than those generated by a universe-wide model while still retaining sufficient degrees of freedom.

Given the use of PCA and separate regressions for different size and value categories, an exhibit demonstrating the contribution of each underlying variable to trade-level score distribution is warranted. The whole universe of trade-level scores from 01/01/1997 to 12/31/2011 was regressed on the original input variables and all relevant controls discussed above. The results in Table A1 illustrate the direction, magnitude, and significance of each variable in driving the scores assigned to both buy and sell transactions in our sample. Momentum and number of shares are both positively and significantly associated with higher scores in both buy and sell transactions while trade value and trade ratio are negatively related in each case. Transaction size as a percentage of holdings, the blackout flag, the proven insider flag, the direct trade flag, and the 30-day consensus variable were all positively related with model score in the case of buys but negatively so in the case of sells; all cases were significant at the 0.05 or 0.01 level.

Next, we aggregate scores at the company level. In order to take into account signals from previous filings within a company, aggregation logic is employed. An aggregated score is created by taking a time-weighted average of the previous 91 days' trade scores for a given company. This approach incorporates historical as well as concurrent information while dealing with issues arising from conflicts between buy and sell scores during the same week.

Scores decay (weaken in magnitude) through time whenever a company experiences a cessation in transaction activity. This occurs because the original signal that generated the score for a company weakens as a function of time. Companies that do not have recent insider trading activity (i.e., no historical activity or transactions for a minimum of 24 weeks) are assigned an null score. A 4-week period is required for a score to decay to the next level (e.g., from a 10 to a 9 or from a 3 to a 4). However, any null company scores are revised back to a value within the 1 to 10 scale immediately upon receipt of information on eligible new insider trading activity. This also means that when a company does not have any filings in a given week, and less than 4 weeks have passed since the most recent score was created, the most recent score for the firm will be populated for the firm in the given week.

The decay logic is a simple, straightforward proxy for modeling the persistence of excess returns following insider trading signals. It should be emphasized that the duration of the market reaction to signals from insider activity varies across firms and time. Thus, purchasing (selling) a security immediately following a new or revised positive (negative) score will maximize the probability of earning excess returns. Purchasing (selling) a security based on a decayed positive (negative) score will result in a strong, but reduced, probability of earning excess returns (relative to purchase/sale decisions based on new or revised scores).

For each of the largest 5000 companies ranked by market cap, each week the model generates either a missing score (due to no relevant data to construct a score) or a score ranging from 1 (strong sell) to 10 (strong buy). A non-missing score provides a ranking based on a stock's expected future excess performance over a 1–6 month holding period. Out-of-sample return spreads between 1 and 10 scores for the 1997–2011 period are 4.4% at 3 months, 8.6% at 6 months, and

Not for Distribution

10.7% at 1 year, all significant at the 99.99% level.

To illustrate the effectiveness of the model in discerning insiders acting on positive or negative information, three firms from different time periods, sectors, and market capitalization ranges are presented to provide some insight into the way in which the model determines scores.

Ciena Corporation (NASDAQ: CIEN) is a provider of communications networking equipment, software and services that support the transport, switching, aggregation and management of voice, video and data traffic. ITM gave the company a score of 1 (sell signal) on 07/13/2001. The model had picked up strong negative sentiment from the company's Chief Technology Officer, selling 1.8 times as many shares as expected. The trade was accompanied by consensus selling from other executives around the same time. The sale of shares valued over $3,000,000 accounted for 33% of the executive's holdings. The resulting yields were a −12.2% 1-month return, −54.3% 6-month return, and −83.7% 1-year return. On the other hand, the firm received a score of 10 (buy signal) just over a year later on 10/11/2002 after a director bought 20,000 shares. Again, this buy accounted for a third of the director's holdings in the company and was a larger trade than usual. The timing of the trade was important as the stock was down almost 80% over the previous year. The 1-month, 6-month, and 1-year returns were 49.1%, 69.1%, and 143.0%, respectively.

Southwest Gas Corporation (NYSE: SWX) is engaged in the business of purchasing, distributing, and transporting natural gas in portions of Arizona, Nevada, and California. On 04-07-2006, the firm was scored at a 10 (buy signal) by ITM. Strong buying activity from two different directors increased their combined holdings by almost 44%. The returns for 1-month, 6-month, and 1-year were 4.5%, 24.4%, and 43.2%, respectively. On 05-23-2008, the firm's executives exhibited a different sentiment ITM gave the shares a score of 1. The company's president, Chief Technology Officer, and Treasurer had all made very bearish trades in the previous 2 months. These strong consensus trades each trade constituted 7–14% of holdings for a total sale of $260,000. The 1-month, 6-month, and 1-year returns were −1.3%, −21.4%, and −33.4%, respectively.

Jones Lang LaSalle Incorporated (NYSE: JLL) provides integrated real estate and investment management knowledge on a local, regional and global level to owner, occupier, and investor clients. On 06-05-2003, a director bought over $136,000 worth of company shares, yielding a score of 10 (buy signal) on 06-13-2003. The trade came after heavy downward momentum and constituted a buy of 18% of the insider's total shares. The firm's 1-month, 6-month, and 1-year returns were 1.1%, 30.7% and 64.8%, respectively. The stock continued its rise through much of 2007, however, on 03-21-2008 the model identified a bearish sale by one of the company's officers and assigned the company a score of 1 (sell signal). The $550,000 sale reduced the executive's holdings by 37% and was a much larger sale than typically made by the insider. The 1-month, 6-month, and 1-year returns for the firm's stock were 6.2%, −39.7% and −69.1%, respectively.

In order to justify the complexity of the model, we present findings that represent a demonstrable improvement over those generated by a parsimonious factor already in existence, namely, the opportunistic insider model of Cohen *et al.* (JF, 2010). The model of Cohen *et al.* (2010) identifies those insiders with trading in a given month for each of the preceding 3 years as "routine" while all other insiders are labeled as "opportunistic". This classification is made at the beginning of each year and all subsequent trades by insiders during the following year are classified as either routine

Not for Distribution

or opportunistic based on the classification of the insider making them.

Event study returns demonstrate two notable improvements of our model over the parsimonious factor: (i) a distinct improvement in performance of the factor on both a mean excess and median return basis, and (ii) a marked increase in coverage of 70,149 positive and negative observations for ITM compared to 57,266 for the model of Cohen *et al.* (2010) (see Table A2). The second improvement is a result of the fact that the Cohen factor requires 3 years of prior trades in order to rank an insider and, therefore, their trading activity, while ITM does not require prior history in order to render a score for any given transaction. Additionally, ITM provides a score distribution from 1 to 10, allowing for greater discernibility of differently categorized trades.

In addition, we attempt to demonstrate that the information captured in the parsimonious factor is already present in the ITM signal. This is accomplished by reparameterizing our model with the opportunistic and routine flags from Cohen *et al.* (2010) included as additional variables in the initial model configuration. Results in Table A2 demonstrate the negligible difference between the event study return distributions of the standard ITM and its modified counterpart. In short, ITM not only captures the signal present in a parsimonious factor from concurrent literature, but also markedly improves on both its coverage and performance in an event study context.

So while ITM is itself valuable we do not believe that it can or would be used in isolation to form well-balanced and optimized portfolios. Most insiders do not trade quarterly or even yearly. When insiders do trade, many of their trades are irrelevant. The result is an insider trading model that does not have a score for the majority of companies in most weeks or quarters. To that end, we choose not to force a distribution on the insider trading scores. Instead, we allow the expected value from the in-sample period associated with the specific type of transactions to determine the model score. Understanding this limitation, we enhance ITM with a multi-variable earnings quality signal, EQM, to ensure that we maximize the power of the insider trading signal and create a factor that is investable in a portfolio context.

A significant portion of the excess returns captured by modeling insider trading stems from insiders' ability to manage earnings and time reversals in accruals. Aboody *et al.* (2005) report that insiders trade more profitably in firms with higher exposure to the earnings quality factor. Their results suggest that the exercise of discretion by insiders reduces the effectiveness of the information contained in publicly available accruals data. Furthermore, Beneish and Vargus (2002) find evidence that insiders' trading behavior is informative about the valuation implications of accruals. Their evidence suggests that opportunistic earnings management by insiders is a partial explanation for the accrual mispricing phenomenon. Their work also demonstrates the economically significant profitability of a trading strategy based upon these signals, and that these signals dominate strategies based on either insider trading or earnings quality in isolation.

Perhaps more importantly, Veenman (2012) finds that disclosures of equity purchases by U.S. insiders trigger more positive market reactions for firms with lower quality accruals. The evidence suggests that the strength of this effect is positively associated with the magnitude of insider purchases and the degree of information uncertainty present in the publicly available accruals data. Additionally, Wang (2013) investigates the informativeness of insider trades conditional on managerial ability, proxied for by information asymmetry and reporting practices. These findings indicate that insider trading signals are more

Not for Distribution

predictive of earnings breaks for insiders in firms with lower quality of information and reporting.

To summarize, we complete ITM by linearly combining it with EQM, a well-documented and commercially available earnings quality signal with a significant out-of-sample period. The result is the LIT factor[3] (Table A3):

$$\text{LIT} = 0.7 * \text{ITM} + 0.3 * \text{EQM}. \tag{1}$$

We demonstrate that the LIT factor is generating alpha and not simply exposure to standard risk factors. To this end, we leverage the Carhart four-factor model to isolate the monthly alpha of portfolios constructed using securities with scores from each of the LIT score buckets, 1–10, respectively. While portfolios constructed using stocks with scores in the lower half of the distribution generally do not exhibit statistically significant alphas, those in the upper half do demonstrate monotonically increasing monthly alphas from scores 6 (39 basis points) to 10 (231 basis points) (Table A4).

LIT in isolation produces portfolios that are significant and compelling (see Table A5). However, one of our primary goals is to test the veracity of LIT in the context of an existing fundamental stock selection model. Next, we discuss the details of the USER model and then present results for both LIT and the combination of LIT and USER.

3 A general stock selection model for the United States equity market

The United States Expected Return model of Guerard *et al.* (2012) leverages the work of Markowitz and several others. In 1991, Markowitz headed the Daiwa Securities Trust Global Portfolio Research Department. The Markowitz team estimated stock selection models using Graham and Dodd (1934) fundamental valuation variables, earnings, book value, cash flow and sales, and relative variables, defined as the ratio of the absolute fundamental variable ratios divided by the 60-month averages of the fundamental variables. Bloch *et al.* (1993) reported a set of some 200 simulations of United States and Japanese equity models. Guerard *et al.* (2012) extended a stock selection model originally developed and estimated in Bloch *et al.* (1993), adding a Brush (2001, 2007)-based price momentum variable, taking the price at time $t-1$ divided by the price 12 months ago, $t-12$, denoted PM, and the consensus ($I/B/E/S$) analysts' earnings forecasts and analysts' revisions composite variable, CTEF, to the stock selection model.[4]

$$\begin{aligned}\text{TR}_{t+1} = {} & a_0 + a_1\text{EP}_\text{t} + a_2\text{BP}_\text{t} + a_3\text{CP}_\text{t} \\ & + a_4\text{SP}_\text{t} + a_5\text{REP}_\text{t} + a_6\text{RBP}_\text{t} \\ & + a_7\text{RCP}_\text{t} + a_8\text{RSP}_\text{t} + a_9\text{CTEF}_\text{t} \\ & + a_{10}\text{PM}_\text{t} + e_\text{t}\end{aligned} \tag{2}$$

where:

$$\begin{aligned}
\text{EP} &= \text{[earnings per share]/[price per share]} \\
&= \text{earnings–price ratio} \\
\text{BP} &= \text{[book value per share]/[price per share]} \\
&= \text{book–price ratio} \\
\text{CP} &= \text{[cash flow per share]/[price per share]} \\
&= \text{cash flow–price ratio} \\
\text{SP} &= \text{[net sales per share]/[price per share]} \\
&= \text{sales–price ratio} \\
\text{REP} &= \text{[current EP ratio]/[average EP ratio over the past 5 years]} \\
\text{RBP} &= \text{[current BP ratio]/[average BP ratio over the past 5 years]} \\
\text{RCP} &= \text{[current CP ratio]/[average CP ratio over the past 5 years]} \\
\text{RSP} &= \text{[current SP ratio]/[average SP ratio over the past 5 years]}
\end{aligned}$$

Not for Distribution

$$\begin{aligned} \text{CTEF} &= \text{consensus earnings-per-share} \\ &\quad I/B/E/S \text{ forecast revisions} \\ &\quad \text{and breadth} \\ \text{PM} &= \text{Price Momentum} \quad \text{and} \\ e &= \text{randomly distributed error term} \end{aligned}$$

The USER model is estimated using a weighted latent root regression (WLRR) analysis on Equation (2) to identify variables statistically significant at the 10% level; it uses the normalized coefficients as weights and averages the variable weights over the past 12 months. The 12-month smoothing is consistent with the four-quarter smoothing in Bloch *et al.* (1993). While EP and BP variables are significant in explaining returns, the majority of the forecast performance is attributable to other model variables, namely; relative earnings-to-price, relative cash-to-price, relative sales-to-price, price momentum, and earnings forecast variables. The CTEF and PM variables account for 44% of the model average weights.

We obtain consensus analysts' earnings per share forecast data from $I/B/E/S$ and the earnings, book value, cash flow, depreciation, and sales data from Compustat. The Information Coefficient (IC) is estimated as the slope of a regression line in which ranked subsequent returns are expressed as a function of the ranked strategy, at a particular point of time.

The reader sees in Table A5 that the USER model Information Coefficient is 0.048 and is highly statistically significant, with a t-value of 5.77, in identifying mispriced securities in the Russell 3000 during the 1997–2011 period. We combine the USER with LIT via a simple linear combination, labeled USERLIT (Table A6),[5] where:

$$\text{USERLIT} = 0.50 * \text{USER} + 0.50 * \text{LIT} \qquad (3)$$

USERLIT has a statistically significant IC, with a t-value of 7.39 (see Table A5).

Table A7 shows that USER is also statistically significant in identifying undervalued securities measured by the top–bottom (TB) spread, constructed by subtracting the returns of the bottom decile from the highest decile. The annualized TB spread for USER is 15.53% during the 1997–2011 period with a significant t-statistic of 2.87. The same numbers for LIT are 20.73% and 5.29, respectively. While the USERLIT produces an annualized TB return of 16.31% with a t-statistic of 4.33 (Table A7).

4 Portfolio simulation results with LIT and the USER model

We begin with the USER model simulation to provide a baseline for comparison with LIT for the U.S. market from 1997 to 2011.The USER simulation conditions are identical to those described in Guerard *et al.* (2012), which used monthly optimization with 8% turnover. Guerard *et al.* used 125 basis points, each way, of transactions cost in the U.S.[4]

Next we introduce the LIT into the optimization framework. USER and USERLIT address the Markowitz (1999) question of "Mean and Variance of What?" The portfolio returns of the USER model with MVTar and a lambda of 500 are shown in Table A8. The USER model produces significant outperformance of the Russell 3000 Growth (R3G) benchmark. Furthermore, the inclusion of the LIT increases the Geometric Mean Return, Information Ratio, and Sharpe Ratio in both the EAW and MV portfolios.

We illustrate EAW using several optimization techniques: (1) EAW with no risk controls (NoRC), see Guerard *et al.* (forthcoming); (2) EAW with Tracking Error at Risk, TaR, see Guerard *et al.* (2013); and (3) optimization minimizing total risk, see Markowitz (1959). In the TaR

Not for Distribution

formulation, systematic risk, as measured by 20 orthogonally-estimated betas, and total risk are equally-weighted.

The LIT portfolios are also significant in isolation. However, USERLIT clearly generates the most compelling portfolios. Note the decrease in tracking error with the inclusion of LIT. The power of the USERLIT is made particularly clear in the Mean–Variance (MV) analyses where the Geometric Mean return increases by over 150 basis points annually. The MV Geometric Means, Information Ratios, and Sharpe Ratios exceed those of the EAW analyses (Table A8).

Additionally, the performance of the USERLIT is demonstrated in the context of factor model alphas. We present the results from factor analysis conducted using both the Fama–French (1993) three-factor model and the Carhart (1997) four-factor model in Table A9. As is shown, the monthly alphas calculated for the three- and four-factor models are 0.3118% and 0.4201%, at significance levels of 90% and 95%, respectively (Table A9).

Furthermore, the attribution analysis presented in Table A10 demonstrates the economically significant portion of portfolio return attributable to active management (106 basis points per month), i.e., the value of the underlying quantitative factors driving the portfolio investment decisions. Lastly, the cumulative wealth presented in Chart A1 illustrates how LIT complements the USER stock selection model in a portfolio context (Chart A1).

5 Conclusion

Academic literature conclusively demonstrates that investors can earn superior risk-adjusted returns using intelligently developed insider trading-based signals. And while this task has become more challenging as the field of insider trading research has matured, it is still a worthwhile area of research focus for quantitative asset managers. Understanding the nuances of the available data and constructing unique variables are critical to develop a factor that generates excess returns.

We demonstrate that LIT offers the potential for greater returns relative to risk than using only fundamental and/or expectations data in domestic markets, particularly in the Mean–Variance analysis. This type of research should encourage practitioners who would have previously ignored these signals to reinvestigate the applications of insider trading in their U.S. portfolios.

Appendix A: Tables and charts

Table A1 ITM trade-level scores regressed on underlying model variables.

Universe: *Top 5,000 U.S. firms by market cap annually*
Time: *01/01/1997–12/31/2011*

Tran type	Int.	Mom.	Shares log	Value log	Tran to hold	Cons. 30	Trade ratio	Blkout flag	Proven flag	Direct flag	10b5-1
Buy											
Param.	8.5143	0.0094	0.6362	−0.5804	0.0217	0.0676	−0.0051	0.0802	0.3260	0.0745	—
p-Value	*0.1555*	*0.0002*	*0.0040*	*0.0042*	*0.0061*	*0.0021*	*0.0033*	*0.0077*	*0.0456*	*0.0076*	—
Sell											
Param.	4.0290	0.0097	0.1202	−0.1551	−0.0503	−0.0865	−0.0172	−0.0874	−0.0030	−0.2271	0.1340
p-Value	*0.1128*	*0.0001*	*0.0036*	*0.0036*	*0.0146*	*0.0020*	*0.0025*	*0.0066*	*0.0314*	*0.0062*	*0.0066*

Not for Distribution

Table A2 Event study returns of U.S. stocks for ITM, Cohen *et al.* (2012), and combined factor.

Universe: *Top 5,000 U.S. firms by market cap annually*
Time: *01/01/1997–12/31/2011*

		Observations			Raw return			Excess return			Std. Dev. Raw return			Median Raw return		
Group	Score	*3 Mon*	*6 Mon*	*1 Yr*	*3 Mon*	*6 Mon*	*1 Yr*	*3 Mon*	*6 Mon*	*1 Yr*	*3 Mon*	*6 Mon*	*1 Yr*	*3 Mon*	*6 Mon*	*1 Yr*
Cohen	4	15,318	15,133	14,619	5.02	8.76	17.03	0.87	1.49	2.05	2.77	18.71	36.16	49.91	85.69	0.69
et al.	3	7,208	7,054	6,702	4.86	9.35	15.31	0.85	1.89	3.37	1.95	15.72	32.63	51.07	74.20	0.67
(2012)	2	13,862	13,380	12,390	2.71	5.40	12.05	−0.01	0.20	0.61	1.38	14.55	24.83	38.13	63.65	0.80
	1	46,724	45,510	42,647	2.09	4.21	9.43	−0.22	−0.61	−0.71	−1.28	13.90	24.64	36.87	55.75	0.74
	4	44,039	43,350	41,410	7.12	13.80	25.95	0.95	1.85	3.26	5.87	19.12	35.00	57.36	97.56	1.44
ITM	3	154,590	152,339	145,701	5.86	11.57	23.62	0.33	0.70	1.32	2.70	16.91	31.55	51.45	89.32	0.97
	2	215,087	209,755	196,624	3.29	6.62	13.32	−0.18	−0.36	−0.41	−0.72	14.63	26.13	40.10	65.59	0.89
	1	31,167	30,627	28,739	3.43	7.52	16.63	−0.69	−1.41	−2.03	−2.78	17.69	31.62	48.21	86.90	0.37
ITM	4	44,156	43,481	41,528	7.00	13.63	25.66	0.92	1.79	3.18	5.59	19.07	34.97	57.26	97.21	1.43
+	3	154,515	152,263	145,639	5.86	11.57	23.70	0.34	0.70	1.32	2.76	16.90	31.54	51.35	89.37	0.97
Cohen	2	215,270	209,905	196,779	3.27	6.62	13.29	−0.20	−0.38	−0.42	−0.77	14.59	26.22	40.17	65.56	0.88
	1	31,212	30,679	28,784	3.36	7.30	16.55	−0.62	−1.41	−2.10	−2.68	17.70	30.73	47.29	87.86	0.42

Not for Distribution

Table A3 LIT weighting scheme *r*-squared analysis.

Universe: *Top 5,000 U.S. firms by market cap annually*
Time: *01/01/1997–12/31/2011*

ITM Weight in LIT (%)	3-month raw	6-month raw	3-month excess	6-month excess
10.0	0.002095390	0.003024543	0.000417866	0.000600280
20.0	0.002197530	0.003201103	0.000466151	0.000672344
30.0	0.002328791	0.003419033	0.000546028	0.000785265
40.0	0.002423816	0.003583670	0.000608482	0.000870915
50.0	0.002470320	0.003700130	0.000654595	0.000942832
60.0	0.002515996	0.003804353	0.000693478	0.001009739
70.0	0.002542271	0.003871894	0.000744523	0.001072728
80.0	0.002487436	0.003830576	0.000741898	0.001074470
90.0	0.002456122	0.003810200	0.000748613	0.001089921

Table A4 Four-factor analysis of LIT score-based portfolios.

Universe: *Top 5,000 U.S. firms by market cap annually*
Time: *01/01/1997–12/31/2011*

LIT	Monthly alpha	MKT-RF beta	SMB beta	HML beta	MOM beta
10	0.0231***	0.9937***	0.8544***	0.5559***	−0.1822**
9	0.0164***	0.9506***	0.7657***	0.3646***	−0.2901***
8	0.0144***	0.8096***	0.6590***	0.4181***	−0.3377***
7	0.0079***	0.8482***	0.5719***	0.4186***	−0.1905***
6	0.0039***	0.9377***	0.4883***	0.3816***	−0.1381***
5	0.0009	0.9197***	0.6054***	0.2509***	−0.1094***
4	−0.0028*	1.0116***	0.6380***	0.1834***	−0.0257
3	−0.0035	1.0735***	0.5269***	−0.0732	−0.1541***
2	−0.0030	0.8900***	0.7150***	0.0054	−0.2524***
1	−0.0118	0.4638**	0.7848***	−0.1252	−0.8249***

Asterisks denote significance at the 99% (***), 95% (**), and 90% (*) levels respectively.

Table A5 Information coefficients of U.S. stocks for LIT, USER and USERLIT.

Universe: *U.S. Russell 3000*
Time: *01/01/1997–12/31/2011*

Model	Information coefficient	*t*-Statistic
USER	0.048	5.77
LIT	0.031	9.25
USERLIT	0.030	7.39

Not for Distribution

Table A6 USERLIT weighting scheme performance table.

Universe: *Top 5,000 U.S. firms by market cap annually*
Time: *01/01/1997–12/31/2011*

	Portfolio Performance			vs. Style Benchmark						vs. Russell 3000 Growth					
LIT weight in USERLIT	Ann Ret (%)	Cum Ret (%)	Std Dev (%)	Ann Ex Ret (%)	Cum Ex Ret (%)	IR	Sig Lev (%)	Exp Var (%)	TE (%)	Ann Ex Ret (%)	Cum Ex Ret (%)	IR	Sig Lev (%)	Exp Var (%)	TE (%)
10.0%	10.18	321.17	22.34	5.73	230.39	0.85	99.74	90.85	6.76	6.12	240.72	0.65	98.78	82.40	9.41
20.0%	9.59	289.16	21.47	5.11	197.54	0.83	99.69	91.72	6.18	5.53	208.70	0.62	98.50	82.90	8.88
30.0%	10.08	315.74	20.47	5.33	216.71	0.88	99.80	91.26	6.05	6.02	235.28	0.69	99.13	82.25	8.67
40.0%	10.19	321.99	20.67	5.42	222.17	0.91	99.84	91.71	5.95	6.13	241.54	0.71	99.21	82.54	8.66
50.0%	11.32	390.83	20.51	6.61	292.83	1.07	99.95	90.93	6.18	7.26	310.37	0.84	99.72	82.48	8.62
60.0%	10.73	353.32	20.30	5.77	248.32	0.92	99.85	90.52	6.25	6.67	272.86	0.74	99.38	80.60	9.02
70.0%	9.31	274.26	19.72	4.14	163.20	0.71	99.22	91.24	5.84	5.25	193.81	0.60	98.20	81.00	8.76
80.0%	8.87	252.72	19.45	3.43	133.49	0.61	98.40	91.75	5.59	4.81	172.27	0.57	97.79	82.11	8.42
90.0%	9.68	293.76	19.10	4.26	175.02	0.69	99.12	89.63	6.15	5.62	213.31	0.64	98.68	80.35	8.78

Not for Distribution

Table A7 Top/bottom decile spreads (TB) of U.S. stocks for LIT, USER, and USERLIT.

Universe: *U.S. Russell 3000*
Time: *01/01/1997–12/31/2011*

Model	Annualized top/bottom decile spread (%)	*t*-Statistic
USER	15.53%	2.87
LIT	20.73	5.29
USERLIT	16.31	4.33

Table A8 Risk and return of U.S. stocks for LIT, USER, and USERLIT.

Universe: *U.S. Russell 3000*
Benchmark: *U.S. Russell 3000 Growth*
Time: *01/01/1997–12/31/2011*

Model	Geometric mean (%)	Sharpe ratio	Information ratio	Tracking error (%)
APT risk model and optimizer, EAW with no risk control (NoRC) optimization technique				
USER	7.83	0.22	0.45	8.53
LIT	12.38	0.46	0.81	10.46
USERLIT	8.78	0.30	0.55	8.75
R3G	3.95	0.06	—	—
APT risk model and optimizer, EAW with tracking error at risk (TaR) optimization technique				
USER	8.55	0.24	0.49	9.32
LIT	10.46	0.35	0.61	10.69
USERLIT	9.25	0.31	0.57	9.28
R3G	3.95	0.06	—	—
APT risk model and optimizer, EAW with Markowitz (1959) optimization technique				
USER	8.41	0.23	0.43	10.36
LIT	13.29	0.57	0.76	12.32
USERLIT	10.53	0.40	0.68	9.62
R3G	3.95	0.06	—	—
APT Risk Model and Optimizer, MV with Markowitz (1959) Optimization Technique				
USER	9.65	0.27	0.44	12.97
LIT	15.63	0.70	0.80	14.68
USERLIT	11.91	0.47	0.67	11.85
R3G	3.95	0.06	—	—

Not for Distribution

Table A9 Three- and four-factor analysis of USERLIT.

Universe: *Top 5,000 U.S. firms by market cap annually*
Time: *01/01/1997–12/31/2011*

Model	Monthly alpha (%)	MKT-RF beta	SMB beta	HML beta	MOM beta
Three-factor	0.3118*	0.9815***	0.4697***	0.1437***	—
Four-factor	0.4201**	0.9055**	0.5039**	0.0892*	−0.1732***

Asterisks denote significance at the 99% (***), 95% (**), and 90% (*) levels respectively.

Table A10 USERLIT attribution report.

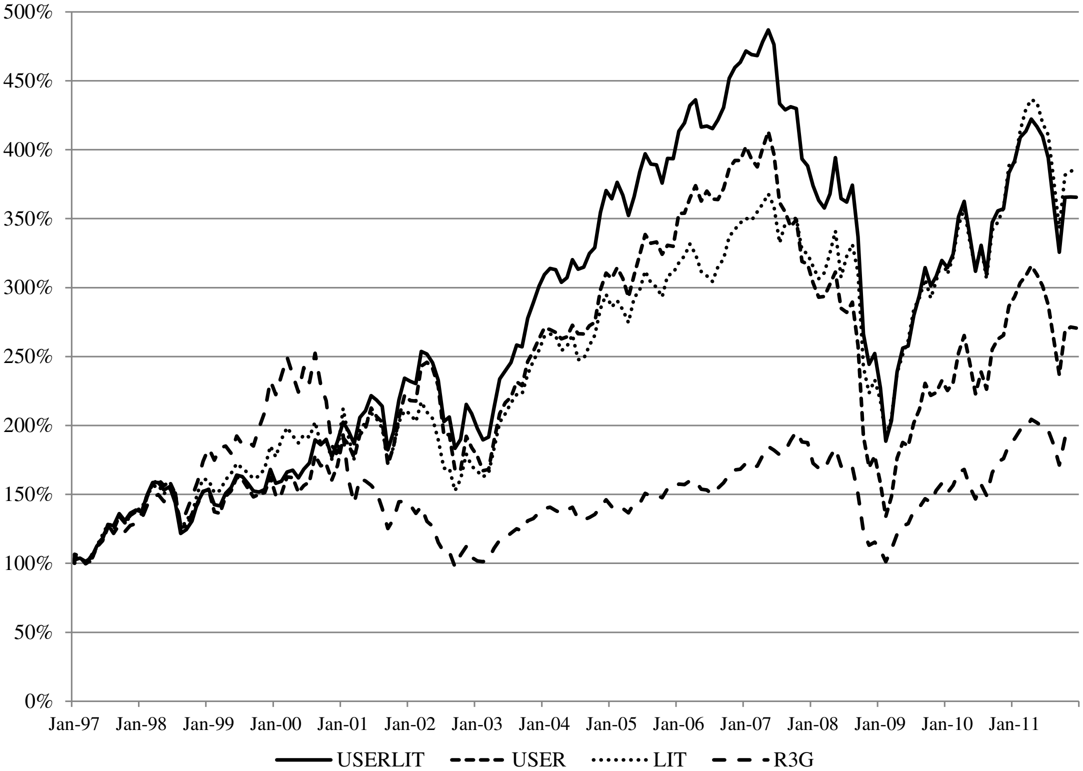
Universe: *Top 5,000 U.S. firms by market cap annually*
Time: *01/01/1997–12/31/2011*

	Return contribution (%)										
	Risk free [1]	Benchmark [2]	Expected active [3]	Market timing [4]	Risk indices [5]	Industries [6]	Asset sel. [7]	Tran cost [8]	Except actual [4 + ··· + 8] [9]	Active [3 + 9] [10]	Managed [2 + 10] [12]
Mean	0.23	0.49	0.00	0.02	0.43	−0.07	0.43	−0.25	0.57	0.57	1.06
Std Dev	0.17	5.59	0.08	0.92	2.69	1.14	2.16	0.04	3.25	3.24	5.95
Min	0.00	−17.89	−0.16	−2.81	−6.28	−4.72	−6.86	−0.41	−7.10	−7.15	−20.10
Max	0.52	12.60	0.21	3.12	12.41	4.83	7.26	−0.17	13.96	13.91	20.48

Not for Distribution

Chart A1 Portfolio performance of U.S. stocks for USER, LIT, and USERLIT.

Universe: *U.S. Russell 3000*
Time: *01/01/1997–12/31/2012*



Appendix B: The earnings quality model

The latest academic research demonstrates that the market does not fully impound information about earnings quality at the time that detailed financial statement data are released. That is, a statistically-based approach to analyzing earnings quality can yield profitable investment and trading strategies. The logical extension of this research from the perspective of the practitioner was to develop a robust model designed to optimize the excess returns that can be realized from an earnings quality strategy.

The earnings quality model (EQM) is a quantitative factor that measures earnings quality across a broad spectrum of companies. The model provides two weekly scores ranging from 1 (strong sell) to 8 (strong buy) for each of the top 5,000 domestic companies ranked by market capitalization (and includes ADRs within a similar capitalization range). The Long-Term Score provides a 1–8 ranking based on a stock's expected future performance over a 3–12 month holding period. The Short-Term Score ranks each stock based on its expected future performance over a 1–3 month holding period. A granular, percentile 1 to 100 version of both the Long-Term Score and Short-Term Score is also generated.

EQM is derived objectively—not subjectively—through statistical analysis of accrual and cash flow components of earnings. For example, Cash Conversion Cycle is a strong indicator of a company's ability to generate cash flow, and is

Not for Distribution

often used in a more qualitative earnings quality analysis. This measure was extended to our entire universe of companies and yielded highly predictive results.

The model was developed using rigorous statistical methods to ensure that a robust factor generates excess returns on a standalone basis while also capturing a unique dimension of returns not captured by other quantitative factors. More specifically, the model was constructed using a multiple regression approach (including regressors from academic research and our own theoretically sound proprietary earnings quality constructs) estimated in pooled time series, cross section for 13 sector categories. Each separate sector model incorporates the most important dimensions of earnings quality for that segment of the market. When considered together, these dimensions or "sub-factors" provide a means of reliably ranking firms monotonically according to both their expected mean and median excess returns. The end product is a highly unique factor with exceptional returns and low correlation in relation to other commonly used factors.

All models are developed using a disciplined scientific approach, which can be characterized as follows:

— Variable Specification—We begin by carefully specifying each variable to ensure proper measurement and scaling. When more than one specification is defensible, we choose the simplest specification on the theory that simplicity will yield more generalizable results.
— Modeling Techniques—Each model is estimated using relatively simple linear and nonlinear regression techniques. Again, we believe that simplicity is the key to generalizability.
— Sensitivity Analyses—All models are subjected to sensitivity analyses to determine whether or not our results are impacted by outliers, changes in regimes, alternative variable specifications and modeling techniques, and so on.
— Proper Use of In-Sample and Out-of-Sample Periods—Each model is estimated using data from a strict in-sample period. The model is then tested (for generalizability, stability, and so on) in an out-of-sample period.
— Control for Potential Threats to Internal and External Validity—Our research efforts are designs to control for common threats to internal and external validity in financial engineering studies (such as survivorship bias, hindsight bias, and selection bias).

EQM has been extensively back-tested across a variety of stock universes and time periods in order to ensure optimal, generalizable results. The model produces highly significant excess returns, performs extremely well both in- and out-of-sample, and has a low correlation with other commonly used quantitative factors.

Appendix C: Portfolio construction and risk estimation with the USER model

The objective in portfolio construction and management has been to achieve the maximum return for a given level of risk or the minimum risk for a given level of return (Markowitz, 1952, 1956, 1959; Bloch *et al.*, 1993). We briefly review the portfolio construction methodology and techniques in the U.S. versus a Russell 3000 Growth benchmark, using applied U.S. equity investment research in Guerard *et al.* (2012). We find that mean–variance techniques, which have existed for six decades, can be used to create portfolios generating statistically significant asset selection. In this experiment we examine mean–variance and enhanced index-tracking techniques. First, we discuss and examine the relationship of a Markowitz mean–variance (MV) portfolio construction model (Markowitz, 1952, 1956, 1959;

Not for Distribution

Markowitz and Todd, 2000), with a fixed upper bound on security weights, and a Markowitz (1987) enhanced-index tracking (EIT) portfolio construction model in which security weights are an absolute deviation from the security weight in the index.

We refer to the absolute deviation from the benchmark weight-enhanced index portfolio construction weight as the equal active weighting (EAW) portfolio construction model. In constructing efficient portfolios the security weights are the primary decision variables to be solved. Second, we test whether an MV optimization technique using the portfolio variance as the relevant risk measure dominates the risk–return trade-off curve using a variation of the optimization model that emphasizes systematic (or market) risk. A PCA model is used to estimate and monitor portfolio risk. A measure of the trade-off between the portfolio's expected return and risk (as measured by the portfolio standard deviation) is typically denoted by the Greek letter lambda (λ). Generally, the higher the lambda, the higher the ratio of portfolio expected return to portfolio standard deviation. We assume that the portfolio manager seeks to maximize the portfolio Geometric Mean (GM) and Sharpe Ratio as put forth in Latane (1959) and Markowitz (1959, 1976).[6i] We use a multifactor risk.

The portfolio expected return, denoted by $E(\mathrm{R_p})$, is calculated by taking the sum of the security weights multiplied by their respective expected return. The portfolio variance is the sum of the weighted security covariances.

$$E(\mathrm{R_p}) = \sum_{i=1}^{N} w_{\mathrm{i}} E(R_i) \tag{C.1}$$

$$\sigma_{\mathrm{p}}^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{\mathrm{i}} w_{\mathrm{j}} \sigma_{\mathrm{ij}} \tag{C.2}$$

where N is the number of candidate securities, w_i is the weight for security i such that $\sum_{i=1}^{N} w_i = 1$ indicating that the portfolio is fully invested, and $E(R_i)$ is the expected return for security i. The Markowitz framework measures risk as the portfolio standard deviation, a measure of dispersion or total risk. One seeks to minimize risk, as measured by the covariance matrix in the Markowitz framework, holding constant expected returns.

We extend the MV approach via an enhanced index tracking optimization technique and a tracking error at risk optimization technique. Markowitz (1987) and Markowitz and Todd (2000) rewrite the general portfolio construction model variance, V, to be minimized as:

$$V = (X - W)^{\mathrm{T}} C (X - W) \tag{C.3}$$

where $W^{\mathrm{T}} = (W_1, \ldots, W_n)$ is the vector of weights of an index of returns, X are the portfolio weights, and $r^{\mathrm{T}} = (r_1, \ldots, r_n)$ is the vector of security returns.

The total excess return for a multiple-factor model for security j, at time t, dropping subscript t for time, may be written as:

$$R_j = \sum_{k=1}^{K} \beta_{jk} \widetilde{f}_k + \widetilde{e}_j. \tag{C.4}$$

The nonfactor, or asset-specific return on security j, is the residual risk of the security after removing the estimated impacts of the K factors. The term f_k is the rate of return on factor k. The characterization of portfolio risk requires an accurate estimate of the covariance matrix of security returns. The reader is referred to Rudd and Clasing (1982) and Conner and Korajczyk (2010) for very good expositions of multifactor risk models.

What follows is a brief exposition of the APT model and its empirical implications. The mathematical underpinning of the APT model can be found in Dhrymes *et al.* (1984) and Dhrymes *et al.*

Not for Distribution

(1985a, 1985b). We use the APT risk model and optimizer described in Blin *et al.* (1997) to create portfolios by varying the portfolio lambda. The Markowitz trade-off curve is a Level II test. One seeks to maximize the Geometric Mean, Sharpe Ratios, and Information Ratios of portfolios. The model begins by postulating the return generating function

$$r_t = E_t + f_t B + u_t \tag{C.5}$$

where r_t is an m-element row vector containing the observed rates of return at time t for the m-securities under consideration; E_t is similarly an m-element row vector containing the expected (mean) returns at time t. Finally,

$$v_t = f_t B + u_t \tag{C.6}$$

represents the error process at time t. It is an essential to the APT model that the error process has an idiosyncratic component

$$u_t, \quad t = 1, 2, \ldots$$

and a common component

$$f_t B.$$

It is assumed that

$$\{u_t' : t = 1, 2, \ldots\}$$

is a sequence of independent identically distributed (i.i.d.) random vectors with

$$E(u_t') = 0, \quad \mathrm{Cov}(u_t', f_t') = 0, \quad \mathrm{Cov}(u_t') = \Omega. \tag{C.7}$$

The covariance matrix Ω being *diagonal* and such that

$$0 < \omega_{ii} < \infty, \quad i = 1, 2, \ldots, m. \tag{C.8}$$

Regarding the common component, we note that the form in which it is stated creates an identification problem, since neither f not B is directly observable. We (partly) eliminate this problem by specifying that

$$\{u f_t' : t = 1, 2, \ldots\}$$

is a sequence of k-element i.i.d. random vectors with[7]

$$E(f_t') = 0, \quad \mathrm{Cov}(f_t') = I. \tag{C.9}$$

It is a consequence of the assertions above that

$$\{(r_t - E_t)' : t = 1, 2, \ldots\}$$

is a sequence of i.i.d. random vectors with

$$\begin{aligned} &E[(r_t - E_t)'] = 0, \\ &\mathrm{Cov}[(r_t - E_t)'] = B'B + \Omega = \Psi \end{aligned} \tag{C.10}$$

We further note that

$$\begin{aligned} \mathrm{Cov}(r_{it}, r_{tJ}) &= b_{-i}' b_{\cdot j} & i \neq j \\ &= b_{\cdot i}' b_{\cdot I} + \omega_{ii} & i = j \end{aligned} \tag{C.11}$$

and that the columns of B ($b_{\cdot I}$, which are $k \times 1$) contain information on the covariation of securities.

Notes

1 The term "insider", in the context of U.S. insider trading, refers to any individual who is required by law to file a Form 3, 4, or 5 with the Securities and Exchange Commission whenever they trade in a company's securities. This definition includes officer, director, board member, president, vice president, and other members of a company who own stock of the firm designated as an insider by directors. It also covers parties not directly employed by the company but who may still be privy to material non-public information; this includes family members of executives, funds an executive owns or manages, family trusts, major shareholders, and other related entities.

2 Prior to Sarbanes Oxley, most insiders reported their non-exempt trades by paper filings which were to be post marked by the 10th day of the calendar month following the calendar month of their trade.

3 Tests were conducted to determine the optimal weighting schema in a univariate context. Nine linear combinations of ITM and EQM were created in increments of 10% from 10–90 to 90–10. Returns were then regressed on panel data of each of these nine scores to produce r-squared trade-off curves (see Table A3), demonstrating that the 70–30 weighting was optimal. This approach was

Not for Distribution

performed using both raw and sector-size excess returns at both 3 and 6 months. For both raw return iterations the 70–30 dominated all other weightings. In the excess return cases significant improvement in the r-squared trade-off curve peaked at 70–30. It should be noted that a separate analysis was conducted to determine the optimal weighting for the LIT factor in the context of the final portfolio optimization, i.e., which LIT weighting scheme performs best in the final portfolio. In this case, a weight of 80–20 was dominant. Given the nature of the trade-off curve described above anything in the range of a 70–90 percent weighting for ITM in the LIT factor should have prevailed. Again, this optimization approach was not implemented as it introduces the confounding effect of optimizing the LIT factor in the context of the portfolio that is ultimately used to test its efficacy.

[4] Guerard and Mark (2003) found that the consensus analysts' forecast variable dominated analysts' forecasted earnings yield, as measured by $I/B/E/S$ 1-year-ahead forecasted earnings yield, FEP, revisions, and breadth. Guerard (2012) reported domestic (U.S.) evidence that the predicted earnings yield is incorporated into the stock price through the earnings yield risk index. Moreover, CIBF dominates the historic low price-to-earnings effect, or high earnings-to-price, PE.

[5] The equal weighting of LIT and USER to create USER-LIT is justified by the results in Table A6 where the dominant annualized return and Information Ratio of this configuration are apparent with respect to the remaining portfolios on the trade-off curve.

[6] See Markowitz (1959), Chapter 9.

[7] Note that if $\mathrm{Cov}(f_t') = \Phi$, $\Phi > 0$ otherwise arbitrary, then $f_t B$ is indistinguishable from B^o where, for arbitrary non-singular C, $= f_t C$, $B^o = C^{-1}B$.

References

Aboody, D., Hughes, J., and Liu, J. (2005). "Earnings Quality, Insider Trading, and Cost of Capital," *Journal of Accounting Research* **43**(5), 651–673.

Aboody, D. and Kasznik, R. (2001). "Executive Stock Option Compensation and Corporate Cash Payout Policy," Working Paper. Los Angeles: University of California at Los Angeles.

Atkas, N., De Bodt, E., and Van Oppens, H. (2008). "Legal Insider Trading and Market Efficiency," *Journal of Banking & Finance* **32**(7), 1379–1392.

Allen, S. and Ramanan, R. (1990). "Earnings Surprises and Prior Insider Trading: Tests of Joint Informativeness," *Contemporary Accounting Research* **6**(2), 518–543.

Beneish, M. D. and Vargus, M. E. (2002). "Insider Trading, Earnings Quality, and Accrual Mispricing," *The Accounting Review* **77**(4), 755–791.

Bettis, J. C. and Coles, J. L. (1997). "New Evidence on Insider Trading Around Merger Announcements," Unpublished Working Paper. Tempe: Arizona State University.

Bettis, J. C., Vickrey, D., and Vickrey, D. W. (1997). "Mimickers of Corporate Insiders Who Make Large-Volume Trades," *Financial Analysts Journal* 57–66.

Bettis, J. C., Coles, J. L., and Lemmon, M. L. (2000) "Corporate Policies Restricting Trading by Insiders," *Journal of Financial Economics* **57**(2), 191–220.

Bettis, J. C., Bizjak, J. M., and Lemmon, M. L. (2005). "Exercise Behavior, Valuation, and the Incentive Effects of Employee Stock Options," *Journal of Financial Economics* **76**(2), 445–470.

Blin, J., Bender, S., and Guerard, J. B. (1997). "Earnings Forecasts, Revisions, and Momentum in the Estimation of Efficient Market-Neutral Japanese and US Portfolios," *Research in Finance* **15**, 93–114.

Bloch, M., Guerard, J., Markowitz, H., Todd, P. and Xu, G. (1993). "A comparison of Some Aspects of the US and Japanese Equity Markets," *Japan and the World Economy* **5**(1), 3–26.

Brochet, F. (2010). "Information Content of Insider Trades Before and After the Sarbanes-Oxley Act," *The Accounting Review* **85**(2), 419–446.

Brush, J. S. (2007). "A Flexible Theory of Price Momentum," *The Journal of Investing* **16**(1), 36–42.

Brush, J. S. (2001). "Price Momentum: A Twenty Year Research Effort, *Columbine Newsletter*.

Carhart, M. M. (1997). "On Persistence in Mutual Fund Performance," *The Journal of Finance* **52**(1), 57–82.

Carpenter, J. and Remmers, B. (1998). "Stock Price Performance Following Insider Option Exercise," Available at SSRN 85309.

Cheng, Q. and Lo, K. (2006). "Insider Trading and Voluntary Disclosures," *Journal of Accounting Research* **44**(5), 815–848.

Cohen, L., Malloy, C., and Pomorski, L. (2010). "Decoding Inside Information," No. 16454. *National Bureau of Economic Research.*

Conner, G. and Korajczyk, R. A. (2010). "The CAPM, Multi-Factor Risk Models, and the Arbitrage Pricing

Not for Distribution

Theory," J. Guerard, Ed., *Handbook of Portfolio Construction*: *Current Applications of Markowitz Techniques*. New York: Springer.

Dhrymes, P. J., Friend, I., and Bulent Gultekin, N. (1984). "A Critical Reexamination of the Empirical Evidence on the Arbitrage Pricing Theory," *The Journal of Finance* **39**(2), 323–346.

Dhrymes, P. J., Friend, I., Gultekin, M. N., and Bulent Gultekin, N. (1985a). "An Empirical Examination of the Implications of Arbitrage Pricing Theory," *Journal of Banking & Finance* **9**(1), 73–99.

Dhrymes, P. J., Friend, I., Gultekin, M. N., and Bulent Gultekin, N. (1985b). "New Tests of the APT and Their Implications," *The Journal of Finance* **40**(3), 659–674.

Elliott, J., Morse, D., and Richardson, G. (1984). "The Association Between Insider Trading and Information Announcements," *The Rand Journal of Economics* 521–536.

Fama, E. F. and French, K. R. (1993). "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* **33**(1), 3–56.

Fidrmuc, J., Goergen, M., and Renneboog, L. (2006). "Insider Trading, News Releases and Ownership Concentration," *Journal of Finance* **61**, 2931–2973.

Finnerty, J. E. (1976). "Insiders and Market Efficiency," *The Journal of Finance* **31**(4), 1141–1148.

Garfinkel, J. A. (1997). "New Evidence on the Effects of Federal Regulations on Insider Trading: The Insider Trading and Securities Fraud Enforcement Act (ITSFEA)," *Journal of Corporate Finance* **3**(2), 89–111.

Giamouridis, D., Liodakis, M., and Moniz, A. (2008). "Some Insiders are Indeed Smart Investors," Available at SSRN 1160305.

Givoly, D. and Palmon, D. (1985). "Insider Trading and the Exploitation of Inside Information: Some Empirical Evidence," *Journal of Business*, 69–87.

Gosnell, T., Keown, A. J., and Pinkerton, J. M. (1992). "Bankruptcy and Insider Trading: Differences Between Exchange-Listed and OTC Firms," *The Journal of Finance* **47**(1), 349–362.

Graham, B. and Dodd, D. (1934). *Security Analysis*: *Principles and Techniques*. 1st edition.

Guerard, J. B., Xu, G., and Gültekin, M. (2012). "Investing with Momentum: The Past, Present, and Future," *The Journal of Investing* **21**(1), 68–80.

Guerard, J. B. (2012). "Global Earnings Forecasting Efficiency," in John Kensinger, Ed., *Research in Finance* **28**, 19–48.

Guerard, J. B. and Mark, A. (2003). "The Optimization of Efficient Portfolios: The Case for an R&D Quadratic Term," *Research in Finance* **20**, 213–247.

Guerard, J. B., Rachev, Z., and Shao, B. (2013). "Efficient Global Portfolios: Big Data and Investment Universes," *IBM Journal of Research and Development* **57**(5), Paper 11, 1–11.

Guerard, J. B., Markowitz, H., and Xu, G. "Earnings Forecasting in a Global Stock Selection Model and Efficient Portfolio Construction and Management," *International Journal of Forecasting* **31**, 550–560.

Henderson, M. Todd, Jagolinzer, A., and Muller, K. (2010). "Strategic Disclosure of 10b5-1 Trading Plans," Working Paper, University of Chicago.

Huddart, S., Ke, B., and Petroni, K. (2003). "What Insiders Know About Future Earnings and How They Use It: Evidence from Insider Trades," *Journal of Accounting and Economics* **35**(3), 315–346.

Huddart, S. and Lang, M. (2003). "Information Distribution Within Firms: Evidence From Stock Option Exercises," *Journal of Accounting and Economics* **34**(1), 3–31.

Huddart, S., Ke, B., and Shi, C. (2007). "Jeopardy, Nonpublic Information, and Insider Trading Around SEC 10-K and 10-Q Filings," *Journal of Accounting and Economics* **43**(1), 3–36.

Jaffe, J. F. (1974). "Special Information and Insider Trading," *Journal of Business*, 410–428.

Jagolinzer, A. D. (2009). "SEC Rule 10b5-1 and insiders' strategic trade," *Management Science* **55**(2), 224–239.

Jeng, L. A., Metrick, A., and Zeckhauser, R. (2003). "Estimating the Returns to Insider Trading: A Performance-Evaluation Perspective," *Review of Economics and Statistics* **85**(2), 453–471.

Jenter, D. C. (2004). "Understanding Insider Trading by Top Executives," *Financial Executive* **20**(3), 55–57.

Jin, L. and Kothari, S. P. (2005). "Determinants of Management Ownership of Unrestricted Equity: Overconfidence Versus Tax Explanations," in EFA 2005 Moscow Meetings Paper.

Jin, L. and Kothari, S. P. (2008). "Effect of Personal Taxes on Managers' Decisions to Sell Their Stock," *Journal of Accounting and Economics* **46**(1), 23–46.

John, K. and Lang, L. H. P. (2012). "Insider Trading Around Dividend Announcements: Theory and Evidence," *The Journal of Finance* **46**(4), 1361–1389.

Karpoff, J. M. and Lee, D. (1991). "Insider Trading Before New Issue Announcements," *Financial Management*, 18–26.

Not for Distribution

Lakonishok, J. and Lee, I. (2001). "Are Insider Trades Informative?" *Review of Financial Studies* **14**(1), 79–11.

Latane, H. A. (1959). "Criteria for Choice among Risky Ventures," *The Journal of Political Economy* **67**(2), 144–155.

Lin, J.-C. and Howe, J. S. (1990). "Insider Trading in the OTC Market," *The Journal of Finance* **45**(4), 1273–1284.

Loderer, C. F. and Sheehan, D. P. (1989). "Corporate Bankruptcy and Managers' Self-Serving Behavior," *The Journal of Finance* **44**(4), 1059–1075.

Lorie, J. H. and Niederhoffer, V. (1968). "Predictive and Statistical Properties of Insider Trading," *Journal of Law and Economics* **11**, 35.

Markowitz, H. M. (1952). "Portfolio Selection," *The Journal of Finance* **7**(1), 77–91.

Markowitz, H. M. (1956). "The Optimization of a Quadratic Function Subject to Linear Constraints," *Naval Research Logistics Quarterly*, 111–133.

Markowitz, H. M. (1959). "Portfolio Selection: Efficient Diversification of Investment," *Cowles Foundation Monograph*, No. 16, New York: John Wiley & Sons.

Markowitz, H. M. (1976). "Investment in the Long Run: New Evidence for an Old Rule," *Journal of Finance* **31**, 1273–1286.

Markowitz, H. M. (1987). *Mean-Variance Analysis in Portfolio Choice and Capital Markets*. Oxford: Basil Blackwell.

Markowitz, H. M. (July/August 1999). "The Early History of Portfolio Theory, 1600-1960," *Financial Analysts Journal* **55**(4), 5–16.

Markowitz, H. M. and Peter Todd, G. (2000). *Mean-Variance Analysis in Portfolio Choice and Capital Markets*. Vol. 66. Wiley.

Moss, J. and Kohers, T. (1990). "Abnormal Gains for Insiders Trading Prior to Unexpected Corporate Earnings and Dividend Announcements," *Akron Business Review* **21**, 63–74.

Park, S., Jonathan Jang, H., and Loeb, M. P. (1995). "Insider Trading Activity Surrounding Annual Earnings Announcements," *Journal of Business Finance & Accounting* **22**(4), 587–614.

Penman, S. H. (1985). "A Comparison of the Information Content of Insider Trading and Management Earnings Forecasts," *Journal of Financial and Quantitative Analysis* **20**(1), 1–17.

Penman, S. H. (1982). "Insider Trading and the Dissemination of Firms' Forecast Information," *Journal of Business*, 479–503.

Piotroski, J. D. and Roulstone, D. T. (2005). "Do Insider Trades Reflect Both Contrarian Beliefs and Superior Knowledge About Future Cash Flow Realizations?" *Journal of Accounting and Economics* **39**(1), 55–81.

Piotroski, J. D. and Roulstone, D. T. (2004). "The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-specific Information into Stock Prices," *The Accounting Review* **79**(4), 1119–1151.

Pratt, S. P. and DeVere, C. W. (1970). "Relationship Between Insider Trading and Rates of Return for NYSE Common Stocks, 1960–1966," *Modern Developments in Investment Management*, 259–270.

Robbins, A. (2008). "The Rule 10b5-1 Loophole: An Empirical Study," Available at SSRN 941238.

Rozeff, M. S. and Zaman, M. A. (1988). "Market Efficiency and Insider Trading: New Evidence," *Journal of Business*, 25–44.

Rudd, A. and Clasing, H. K. (1982). "Modern Portfolio Theory," in *Principles of Investment Management*. Dow Jones-Irwin: Homewood, Illinois.

Seyhun, H. N. (1986). "Insiders' Profits, Costs of Trading, and Market Efficiency," *Journal of Financial Economics*.

Seyhun, H. N. (1988). "The Information Content of Aggregate Insider Trading," *Journal of Business*, 1–24.

Seyhun, H. N. (1992). "Why Does Aggregate Insider Trading Predict Future Stock Returns?" *The Quarterly Journal of Economics* **107**(4), 1303–1331.

Seyhun, H. N. (1998). Intelligence From Insider Trading.

Veenman, D. (2012). "Disclosures of Insider Purchases and the Valuation Implications of Past Earnings Signals," *The Accounting Review* **87**(1), 313–342.

Verus Analytics (2012). *Quantitative Analysis of Earnings Quality, the Earnings Quality Factor Models*. Scottsdale: Arizona.

Wang, G. (2013). *Managerial Ability and Informed Insider Trading*. Indiana.

Wu, Y. and Zhu, Q. (2011). "When Is Insider Trading Informative?" Available at SSRN 1917132.

Keywords: Insider trading; quantitative portfolios; mean–variance optimization; active portfolio management; multifactor portfolio strategies

Not for Distribution