# The Impact of Investment Operations on Portfolio Performance

CHITO JOVELLANOS

**CHITO JOVELLANOS** is president at FORWARD LOOK, Inc., in Boston, MA.
**cjovellanos@forwardlook.com**

Investment operations (defined as the activities conducted by or on behalf of an asset manager to translate an investment thesis into a working portfolio) are intuitively fundamental to the success of the investment process. In practice however, "ops" has been regarded, by and large, as the investment firm's back-end infrastructure used to deliver and support a broad array of administrative services. As such, the quality of investment operations and the rationale for ongoing improvements have been evaluated mainly in light of expense management, process re-engineering, and/or conformance to industry standards and best practices.

Surprisingly, the more central question of how overall operational efficiency contributes directly to portfolio performance has largely been overlooked. To some extent, this is due to ops receiving only residual management attention since the core focus of investment firms rests with portfolio construction and maintenance, the ongoing product development demands, and client-facing imperatives. More broadly, the sheer complexity of monitoring, evaluating, and managing the numerous components of a typical investment operation are visibly daunting. These components include a vast set of firm-specific functions and industry-wide protocols that span the following:

- marshalling quality research and reference data;
- order management infrastructures and workflows;
- compliance (both pre- and post-trade);
- securities locates (for borrowing and lending);
- collateral management;
- order execution;
- trade management;
- (prime) broker communication;
- custodian communication;
- portfolio and fund accounting;
- reconciliation (across cash, holdings, and transactions);
- settlement.

To date, only a few empirical studies measure how much operational efficiency actually enables the expected returns from an investment portfolio. Typically, these studies express how operational inefficiencies dilute the potential of the underlying investment strategy. Perold [1988] first articulated the concept of the implementation shortfall, which today is mainly discussed in the realm of transaction cost analysis (e.g., Coppejans and Madhavan [2007]), and more recently, transition management (e.g., Obizhaeva [2007]). However, these lines of inquiry seem historically drawn towards one very visible but narrow slice of the overall investment operation—namely, trading and the effects of commissions, market impact, and opportunity costs on realized performance.

As noted earlier, there are clearly more facets to consider when evaluating investment operations. This brief research note adopts this more inclusive posture in the assessment of investment operations, with particular attention to the potential effects of ops activities on portfolio performance. More specifically, we examine two topics that have remained largely unexplored:

1. the relative contribution of all facets of investment operations to the realization of excess return (and implicitly alpha) inherent in the portfolio manager's strategies; and
2. a methodical framework for measuring and articulating firm-specific operational factors that contribute to portfolio implementation shortfalls.

## METHODOLOGY

We re-examined prior projects from our company's previous consulting engagements with investment management firms spanning a 10-year period (October 1999 to August 2009 inclusive). Moreover, we identified those projects where only one very specific operational process was modified during the engagement window (e.g., voluntary corporate actions management), typically in conjunction with a technology implementation in support of that business process (e.g., a corporate actions reconciliation system provided by the custodian or a third-party vendor). For the eligible projects, all other observable investment and operational factors (e.g., strategies, styles, exposures, concentration, asset classes, geographies, performance attribution methodology, benchmarks, portfolio managers, brokers, administrators, custodians, systems, workflows) must have remained constant for the observation period—with the exception of that one operational change that was introduced by the project.

We then compared the reported performance of the affected portfolios before and after the singular process (technology) change. This approach provided a form of *a posteriori* control where only the effects from one imputed operational change were being examined relative to its potential effect on portfolio performance. We were viewing these projects as serendipitous observations obtained "in the wild" that could potentially yield critical evidence from which we could infer the collective impact of the various sleeves of an investment operation on excess returns (relative to the benchmark and gross of fees).

For those projects that satisfied the screening requirement of one and only one operational change involved, we compiled performance histories for the associated portfolios directly from the asset managers as reported to their clients (i.e., relative to the benchmarks and gross of fees). These performance reports reflected a mix of holdings and transaction-based techniques, with data generated at weekly or monthly intervals. To obtain the "before versus after" snapshot of portfolio performance, performance records were noted for the quarter-end prior to the implementation of the one operational change and again for the quarter-end immediately after the operational change was deemed fully in production.

Operational changes typically require several months to be completely implemented. We noted the time span as the observation period for assessing the impact of the operational change. This observation period includes not just the elapsed time needed to physically release the changes into production use, but also any post-implementation monitoring and tuning as needed. For example, the cutover of an equities trading group onto a new order management system may only take a few weeks to a couple of months, whereas the assimilation of a reconciliation system may take almost a year given the number of assets, transaction types, brokers, custodians, administrators, and interested parties involved.

Operational impact was measured only for wholly affected portfolios. For example, the implementation of a new equity trading algorithm would be evaluated against pure equity portfolios (e.g., core; developed markets large cap) but would *exclude* hybrid strategy portfolios that would have been partially affected (e.g., balanced funds).

Our pro-forma protocol in these consulting projects was to conduct an initial workflow analysis of the investment manager's operations. We performed both a top-down review (e.g., working sessions with the firm's personnel) but, just as importantly, also captured a bottom-up view of the operation by sampling the transactions, database entries, and other electronic records (including the ubiquitous spreadsheets and ".csv" files) that flow both within a firm (e.g., end-of-day position files from the trading system into the portfolio accounting system) and also with its various counterparties (e.g., margin variation postings from the prime brokers). A typical list of the data compiled includes the following:

- reference data inputs (e.g., for investment and risk models);
- securities lists (e.g., as generated by the models and/or optimizers);
- compliance rules (e.g., client, regulatory, and firm specific);
- orders, cancels and fills (e.g., from FIX message logs);
- trade summaries (e.g., from order management systems);
- reconciliation records (e.g., cash, positions, and transactions for portfolio accounting);
- settlement records (e.g., custodian confirmations; corporate action notices).

We dissected these data records using a set of proprietary tools to facilitate programmatic analysis. We utilize "record shredders" that isolate tag|value pairs (e.g., ticker|TRI) from various electronic records (e.g., FIX transactions, ISO15022 messages, spreadsheet arrays). This results in normalized data elements that enable us to systematically assess data delivery structures, such as transaction formats (e.g., "packaging" via a SWIFT message), separate from active information content such as securities and counterparty identifiers (i.e., the "payload" like ISINs and BIC codes). In addition, we rely on proprietary "ontologies"[1] that enable operational workflows pertaining to tradable instruments (e.g., valuation of OTC securities), products (e.g., asset allocation strategies), transaction types (e.g., trade confirmation), and counterparties (e.g., prime broker service level agreement) to be formally expressed in fully machine-processable form for automated analysis.

With these data structures in hand, we measured the data operability threshold (DOT) metric (see the Appendix) from the sampled transactions and records. As information flows from the front to the back office, to other firms, industry utilities (e.g., exchanges, clearers, depositories), and vice-versa over the life of a portfolio, DOT quantifies the data mediation effort inherent in accurately mapping information between various data record formats that rely on different contextual regimes, syntaxes, and semantics (e.g., for securities transactions, orders to buy or sell are expressed in FIX format, while trades are reported in SWIFT format, and proprietary or legacy data standards may be in use for the portfolio accounting entries). DOT can be viewed as a more nuanced proxy for the quality of straight-through processing (STP), that is, the lower the threshold for data operability, the greater the likelihood and effectiveness of STP within an investment operation.

## DATA

The project screen yielded 61 sample portfolios from 14 asset managers drawn from a population of 158 portfolios across 21 asset managers. The samples spanned the period from October 1999 to August 2009 inclusive and represent a range of bull and bear markets across varying volatility regimes. We analyzed more than 122 million electronic records across the sampled portfolios. Operational changes required anywhere from 4 to 13 months to be fully implemented. For the sample portfolios, excess returns (relative to the benchmark and gross of fees), together with the corresponding DOT values, were also recorded over the observation period. Exhibit 1 summarizes the key features of these portfolios.

These eligible projects arose purely from commercial engagements that presented themselves to our company at any given time. As such, we had no control over the specific facets of investment operations that are discussed in this research note. For example, we had no opportunity to evaluate alternative investment portfolios that included hard assets (e.g., farmland) or novel instruments (e.g., emission credits), nor did any of the transition portfolios we examined qualify since there were fundamental strategy shifts being applied to these portfolios, which violated our sampling requirement for one and only one operational (i.e., non-investment specific) change being implemented. In summary, 4 major workflow categories of investment operations and the 12 underlying sleeves reflected in this article include the following:

| | |
|---|---|
| **Analytics** | 1. Market Data Management (e.g., commissions, fees, prices)<br>2. Econometric Data Management (e.g., GDP restatements)<br>3. Reference Data Management (e.g., securities, counterparties)<br>4. Risk Modeling (e.g., data quality for factor analysis)<br>5. Portfolio and Trade List Optimization (e.g., fungible names) |
| **Compliance** | 6. Client Guideline Quality (e.g., reframing for precision)<br>7. Pre-Trade Checks (e.g., percentage of ADV)<br>8. Post-Trade Checks (e.g., cross-portfolio limits) |
| **Trading** | 9. Securities Locates (i.e., for shorting)<br>10. Trade Execution (e.g., correctly sequencing fills from multiple venues) |
| **Settlements** | 11. Reconciliation (cash, securities, transactions, corporate actions)<br>12. FX Management (e.g., currency hedges for foreign positions) |

## EXHIBIT 1

**Summary List of Sample Portfolios with Only One Operational Change, October 1999–August 2009**

| | Operational Facet | Obs. Period (mm-yy) | | | Strategy | Securities | Vehicle | Base Curr. | Portf. Value (millions) | Performance (bps) | | | Remediation | DOT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Start | End | mo | | | | | | Start | End | Gain | | |
| **ANALYTICS** | | | | | | | | | | | | | | |
| 1 | Market Data | 09-01 | 05-02 | 9 | emerging mkts | eq, cash | sep acct | GBP | 472 | 32 | 274 | 242 | reduce corp. action data vendors | 0.14 |
| 2 | | 03-03 | 10-03 | 8 | dev. mkts equity | eq, cash, swaps | sep acct | USD | 892 | (2) | 49 | 51 | scrub multiple sources | 0.88 |
| 3 | | 11-05 | 05-06 | 7 | U.S. core equity | eq, cash, swaps | sep acct | USD | 306 | 72 | 170 | 98 | vendor latency | 0.81 |
| 4 | | 01-09 | 06-09 | 6 | asset alloc | eq, bond, cash, swaps | sep acct | USD | 150 | (161) | 22 | 183 | scrub multiple sources | 0.25 |
| 5 | Macro Data | 03-02 | 06-02 | 4 | U.S. bond | bond, cash | sep acct | USD | 902 | 4 | 68 | 64 | econ stats restatements | 0.79 |
| 6 | | 12-04 | 09-05 | 10 | U.S. balanced | eq, bond, cash | sep acct | USD | 958 | (9) | 79 | 88 | sovereign bond data | 0.82 |
| 7 | Reference Data | 01-03 | 07-03 | 7 | asset alloc | eq, bond, opt, fut, cash, swap | sep acct | USD | 386 | 21 | 143 | 122 | deriv identifiers | 0.53 |
| 8 | | 09-03 | 03-04 | 7 | dev. mkts equity | eq, cash, swaps | sep acct | USD | 463 | 94 | 187 | 93 | cross-reference identifiers | 0.80 |
| 9 | | 12-03 | 05-04 | 6 | U.S. small cap blend | eq, cash | sep acct | USD | 237 | 89 | 146 | 57 | issuer data | 0.83 |
| 10 | | 01-04 | 08-04 | 8 | emerging mkts | eq, cash, swaps | sep acct | USD | 118 | (107) | (3) | 104 | issuer data | 0.72 |
| 11 | | 03-04 | 02-05 | 12 | U.S. large cap value | eq, fut, cash, swaps | sep acct | USD | 675 | 67 | 166 | 99 | voluntary corp. action data source | 0.76 |
| 12 | | 07-05 | 12-05 | 6 | global bond | bond, fut, cash | sep acct | EUR | 748 | 19 | 74 | 55 | issuer data | 0.91 |
| 13 | | 06-06 | 01-07 | 8 | global bond | bond, cash, swaps | sep acct | USD | 588 | (22) | 92 | 114 | swap valuations | 0.57 |
| 14 | Risk Model | 02-02 | 09-02 | 8 | U.S. core equity | eq, cash | fund | USD | 1,199 | (12) | 43 | 55 | model metadata | 0.89 |
| 15 | | 08-05 | 06-06 | 11 | global developed | eq, bond, fut, cash | sep acct | USD | 892 | 180 | 274 | 94 | factor management | 0.84 |
| 16 | Portfolio Optimization | 11-03 | 06-04 | 8 | U.S. large cap growth | eq, fut, cash | sep acct | USD | 674 | 72 | 134 | 62 | input sources | 0.85 |
| 17 | Trade List Optimization | 01-04 | 09-04 | 9 | global developed | eq, bond, cash, swaps | sep acct | USD | 493 | 71 | 157 | 86 | modify rebalancing algorithm | 0.74 |
| 18 | | 04-04 | 08-04 | 5 | U.S. small cap value | eq, fut, cash, swaps | sep acct | USD | 102 | 52 | 205 | 153 | normalize broker data | 0.37 |

## EXHIBIT 1 *(continued)*

| | Operational Facet | Obs. Period (mm-yy) | | | Strategy | Securities | Vehicle | Base Curr. | Portf. Value (millions) | Performance (bps) | | | Remediation | DOT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Start | End | mo | | | | | | Start | End | Gain | | |
| **COMPLIANCE** | | | | | | | | | | | | | | |
| 19 | Guideline Quality | 01-02 | 09-02 | 9 | global developed | eq, bond, cash | sep acct | USD | 689 | 164 | 225 | 61 | disambiguate client mandate | 0.85 |
| 20 | | 10-03 | 10-04 | 13 | global bond | bond, cash, swaps | sep acct | USD | 720 | 64 | 156 | 92 | disambiguate client mandate | 0.74 |
| 21 | | 11-05 | 04-06 | 6 | U.S. bond | bond, cash, swaps | sep acct | USD | 517 | (34) | 50 | 84 | disambiguate client mandate | 0.83 |
| 22 | | 09-06 | 12-06 | 4 | U.S. mid cap growth | eq, cash | sep acct | USD | 604 | 62 | 181 | 119 | disambiguate client mandate | 0.58 |
| 23 | | 03-09 | 08-09 | 6 | developed equity | eq, opt, fut, cash, swaps | sep acct | EUR | 881 | 0 | 79 | 79 | disambiguate client mandate | 0.77 |
| 24 | Pre-Trade Checks | 10-99 | 10-00 | 13 | U.S. core equity | eq, fut, cash, swaps | sep acct | USD | 742 | 12 | 103 | 91 | corp actions mgmt | 0.68 |
| 25 | | 05-02 | 12-02 | 8 | U.S. large cap value | eq, cash | sep acct | USD | 664 | (68) | 42 | 110 | corp actions mgmt | 0.62 |
| 26 | | 11-02 | 09-03 | 11 | U.S. bond | bond, cash | sep acct | USD | 203 | (52) | 31 | 83 | exposure calcs | 0.71 |
| 27 | | 11-02 | 09-03 | 11 | U.S. small cap growth | eq, cash | sep acct | USD | 83 | 18 | 149 | 131 | ADV check | 0.41 |
| 28 | | 11-04 | 05-05 | 7 | U.S. small cap value | eq, cash | sep acct | USD | 107 | 58 | 187 | 129 | exposure calcs | 0.38 |
| 29 | | 01-07 | 06-07 | 6 | asset alloc | eq, bond, fut, cash, swaps | sep acct | USD | 433 | 35 | 246 | 211 | real-time validation | 0.34 |
| 30 | | 04-08 | 12-08 | 9 | asset alloc | eq, bond, opt, fut, cash, swap | fund | USD | 972 | (75) | 117 | 192 | exposure calcs | 0.21 |
| 31 | | 05-08 | 11-08 | 7 | U.S. mid cap value | eq, fut, cash, swaps | sep acct | USD | 697 | (132) | (30) | 102 | ADV checks | 0.49 |
| 32 | | 02-09 | 08-09 | 7 | global bond | bond, fut, cash, swaps | sep acct | USD | 807 | 44 | 228 | 184 | exposure calcs | 0.29 |
| 33 | Post-Trade Checks | 07-05 | 12-05 | 6 | U.S. core equity | eq, cash, swaps | sep acct | USD | 706 | 76 | 213 | 137 | firm level checks | 0.56 |
| 34 | | 08-06 | 02-07 | 7 | U.S. bond | bond, fut, cash, swaps | sep acct | USD | 317 | 15 | 217 | 202 | parent level checks | 0.37 |
| 35 | | 05-08 | 09-08 | 5 | global bond | bond, fut, cash, swaps | fund | USD | 794 | 37 | 137 | 100 | firm level checks | 0.58 |

## Exhibit 1 *(continued)*

| | Operational Facet | Obs. Period (mm-yy) | | | Strategy | Securities | Vehicle | Base Curr. | Portf. Value (millions) | Performance (bps) | | | Remediation | DOT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Start | End | mo | | | | | | Start | End | Gain | | |
| **TRADING** | | | | | | | | | | | | | | |
| 36 | Execution | 11-09 | 09-00 | 11 | U.S. small cap growth | eq, cash | sep acct | USD | 98 | 210 | 299 | 89 | IOI management | 0.69 |
| 37 | | 02-00 | 08-00 | 7 | U.S. small cap growth | eq, cash | sep acct | USD | 126 | 184 | 323 | 139 | broker interfaces | 0.46 |
| 38 | | 06-00 | 02-01 | 9 | U.S. small cap value | eq, cash | sep acct | USD | 163 | 74 | 228 | 154 | broker interfaces | 0.41 |
| 39 | | 05-01 | 11-01 | 7 | U.S. small cap growth | eq, cash | sep acct | USD | 219 | (19) | 69 | 88 | optimizer to OMS flow | 0.66 |
| 40 | | 03-03 | 09-03 | 7 | U.S. bond | bond, cash, swaps | sep acct | USD | 365 | 22 | 101 | 79 | broker interfaces | 0.83 |
| 41 | | 06-03 | 11-03 | 6 | U.S. large cap value | eq, cash | fund | USD | 1,082 | 39 | 144 | 105 | OMS implementation | 0.51 |
| 42 | | 06-03 | 01-04 | 8 | U.S. large cap growth | eq, cash | sep acct | USD | 750 | 8 | 103 | 95 | broker interfaces | 0.70 |
| 43 | | 12-03 | 05-04 | 6 | U.S. small cap blend | eq, cash | sep acct | USD | 154 | 31 | 204 | 173 | broker interfaces | 0.38 |
| 44 | | 01-04 | 09-04 | 9 | U.S. small cap blend | eq, cash, swaps | sep acct | USD | 175 | 63 | 165 | 102 | broker interfaces | 0.56 |
| 45 | | 02-04 | 10-04 | 9 | U.S. mid cap growth | eq, cash | sep acct | USD | 401 | 49 | 143 | 94 | algo implementation | 0.69 |
| 46 | | 05-04 | 12-04 | 8 | U.S. core equity | eq, fut, cash, swaps | sep acct | USD | 826 | 77 | 175 | 98 | algo implementation | 0.89 |
| 47 | | 09-04 | 04-05 | 8 | U.S. core equity | eq, fut, cash | sep acct | USD | 678 | 68 | 156 | 88 | algo implementation | 0.86 |
| 48 | | 11-07 | 09-08 | 11 | dev. mkts equity | eq, bond, fut, cash, swaps | sep acct | EUR | 473 | (134) | 23 | 157 | merge fills from MTFs | 0.38 |
| 49 | | 03-05 | 11-05 | 9 | asset alloc | eq, bond, fut, cash, swaps | sep acct | USD | 264 | 19 | 130 | 111 | algo implementation | 0.55 |
| 50 | | 05-05 | 12-05 | 8 | global bond | bond, cash, swaps | sep acct | USD | 355 | 27 | 95 | 68 | OMS workflow | 0.76 |
| 51 | | 10-05 | 06-06 | 9 | emerging mkts | eq, cash, swaps | sep acct | USD | 254 | 112 | 234 | 122 | IOI management | 0.64 |
| 52 | | 03-06 | 10-06 | 8 | balanced | eq, bond, fut, cash, swaps | sep acct | USD | 730 | 65 | 152 | 87 | broker interfaces | 0.62 |
| 53 | | 04-08 | 12-08 | 9 | U.S. bond | bond, fut, cash, swaps | sep acct | USD | 867 | (14) | 79 | 93 | broker interfaces | 0.68 |
| 54 | | 01-09 | 08-09 | 8 | asset alloc | eq, bond, opt, fut, cash, swap | sep acct | EUR | 505 | 17 | 102 | 85 | merge fills from MTF's | 0.67 |

## EXHIBIT 1 *(continued)*

| | Operational Facet | Obs. Period (mm-yy) | | | Strategy | Securities | Vehicle | Base Curr. | Portf. Value (millions) | Performance (bps) | | | Remediation | DOT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Start | End | mo | | | | | | Start | End | Gain | | |
| 55 | Shorting | 07-04 | 02-05 | 8 | U.S. core equity | eq, fut, cash | sep acct | USD | 916 | 33 | 128 | 95 | prime broker interface | 0.73 |
| 56 | | 05-05 | 12-05 | 8 | U.S. mid cap growth | eq, cash, swaps | fund | USD | 628 | (11) | 178 | 189 | prime broker interface | 0.41 |
| 57 | | 05-05 | 01-06 | 9 | U.S. small cap blend | eq, fut, cash, swaps | sep acct | USD | 311 | (22) | 64 | 86 | prime broker interface | 0.65 |
| **SETTLEMENTS** | | | | | | | | | | | | | | |
| 58 | Recon | 03-03 | 12-03 | 10 | global developed | eq, bond, futures, cash | sep acct | USD | 92 | 7 | 113 | 106 | variation margin reporting | 0.49 |
| 59 | | 06-03 | 02-04 | 9 | small cap value | eq, cash, swaps | sep acct | USD | 112 | (183) | (131) | 52 | custodian data | 0.82 |
| 60 | FX | 10-99 | 04-00 | 7 | dev. mkts equity | eq, cash | sep acct | USD | 208 | (14) | 37 | 51 | auto-instructed trades | 0.78 |
| 61 | | 05-04 | 01-05 | 9 | asset alloc | eq, bond, fut, cash, swaps | sep acct | USD | 390 | (2) | 56 | 58 | auto-instructed trades | 0.71 |

*Notes: Grouped by investment operations facet. Portfolio performance (in basis points, relative to portfolio benchmark and gross of fees) reported at start and end of observation period. Portfolio value reflects month-end AuM reported at the midpoint of the observation period. DOT values shown concurrent with performance data reported at the end of the observation period. The following benchmarks were applied to the various portfolios and funds in our sample. No absolute return funds were encountered in this study.*

*U.S. Core Eq MSCI U.S. Prime Market 750 Index; Russell 1000 Value Index; SP 500*

*U.S. Large Cap S&P 500/Barra Value Index; MSCI U.S. Prime Market Value; Russell 1000 Growth Index*

*U.S. Mid Cap MSCI U.S. Broad Market Index; S&P MidCap 400 Index; MSCI US Mid Cap 450 Index; MSCI U.S. Small + Mid Cap 2200 Index; Russell 2800 Index*

*U.S. Small Cap Russell 2000 Index; MSCI U.S. Small Cap 1750 Index*

*Global Developed MSCI EAFE Index; S&P EPAC SmallCap Index; FTSE All-World Index; FTSE Global Sm-Cap ex U.S. Index*

*Emerging Markets MSCI Emerging Markets Index*

*U.S. Bond Lehman/BarCap U.S. Long Government/Credit Bond Index; Lehman/BarCap U.S. Long Government/Credit Float Adjusted Index; Lehman/BarCap U.S. Aggregate Bond Index; BarCap U.S. Universal Index*

*Global Bond Lehman/BarCap Euro-Aggregate Index; Lehman/BarCap Global Aggregate Index FTSE Global Government Bond Indices; FTSE Euro Corporate*

*Balanced (weighted) Dow Jones Wilshire 5000 Index; (weighted) MSCI US Broad Market Index Lehman/BarCap U.S. Aggregate Bond Index; Lehman/BarCap U.S. Aggregate Float Adjusted Index*

*Asset Allocation {blended per above list, including proprietary indices}*

These four workflow categories and their underlying sleeves represent generally recognized processing clusters in an investment operation and are used primarily for convenience in discussing our results.

The portfolios in our sample ran between USD 80 million to USD 1.2 billion in assets under management (AuM), with the parent firm's total AuM ranging from USD 5 billion to USD 100+ billion in AuM. Asset classes included equities (55% across all sample portfolios), corporate and sovereign fixed income (21%), pure cash (in various currencies), and derivatives (both listed and over the counter). Geography covered was global, with approximately 28% of investments in emerging and frontier markets. Portfolio implementation pathways (in support of various investment strategies) spanned long-only, long/short, and managed exposures through derivatives (e.g., equitization, overlays).

## OBSERVATIONS

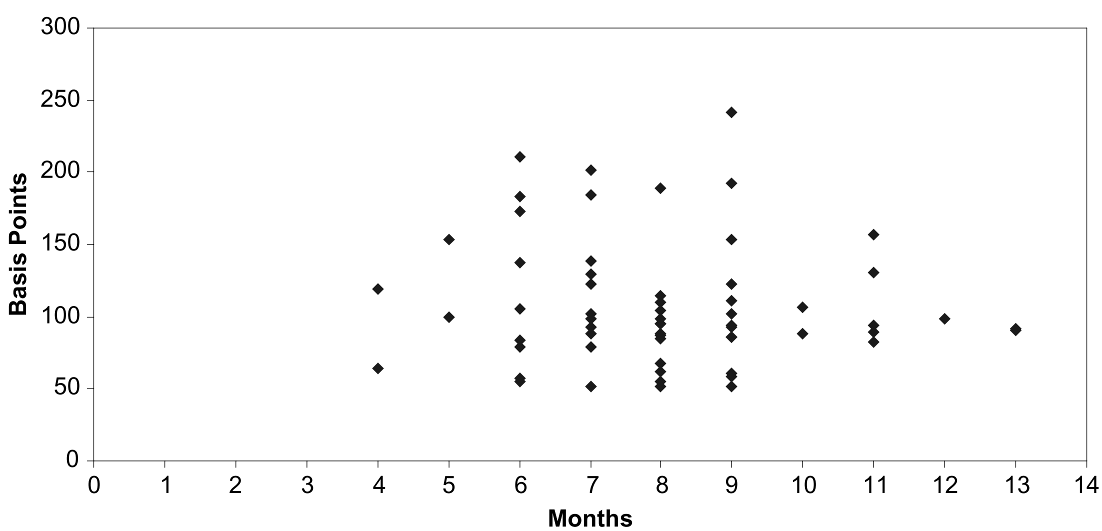
Exhibit 2 plots the portfolio performance improvements over time, expressed in basis points relative to the applicable benchmarks (reported gross of fees). Cluster analysis suggested a centroid indicative of a 127 bp gain within seven months of the operational implementation across the sampled portfolios. There is notable dispersion in the observed values—from 51 bps to 242 bps, which likely reflects the broad range of investment operations activity represented (i.e., from pre-trade analytics through to settlement).

Exhibit 3 presents aggregate performance data for each workflow category described earlier. Ignoring variances in sample size across each of the categories, the implied slopes (judged by eye) of the data points within each category suggests that remediation closer to the portfolio inception stage yields larger potential gains from improvements to investment operations.

Exhibit 4 views aggregate performance data against the corresponding DOT values. The chart supports our intuition that improvements in portfolio performance are closely bound to efficiencies in information transfer. There is a strong negative correlation ($r^2 = -0.89$) between DOT values and the observed gains in portfolio performance. The higher the threshold value for enabling data mediation across electronic records at a firm, the lower the observed performance gains in the sampled portfolios.

Exhibit 5 shows an example of the observed improvements stemming from a given operational change. In this case (see Observation 4 in Exhibit 1), a project to optimize market data usage for a global manager yielded a 183 bp improvement in their portfolio (that utilized long/short equities, sovereign and corporate bonds, futures,

### EXHIBIT 2
**Portfolio Performance Improvements Recorded over the Observation Periods**



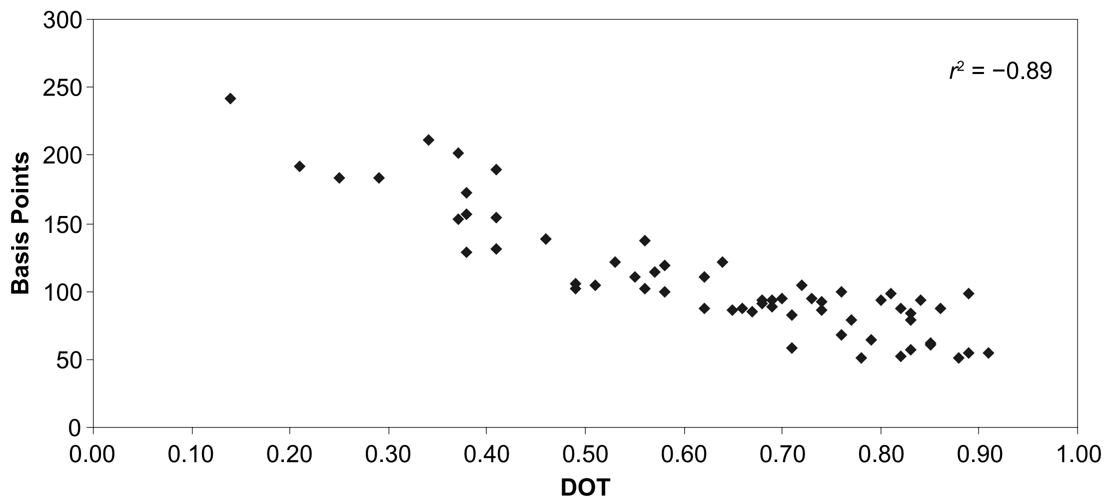

*Note: Expressed in basis points relative to the applicable benchmarks, gross of fees.*

## Exhibit 3

**Aggregate Performance Data Improvements by Workflow Category (in bps, relative to the applicable benchmarks, gross of fees)**


## Exhibit 4

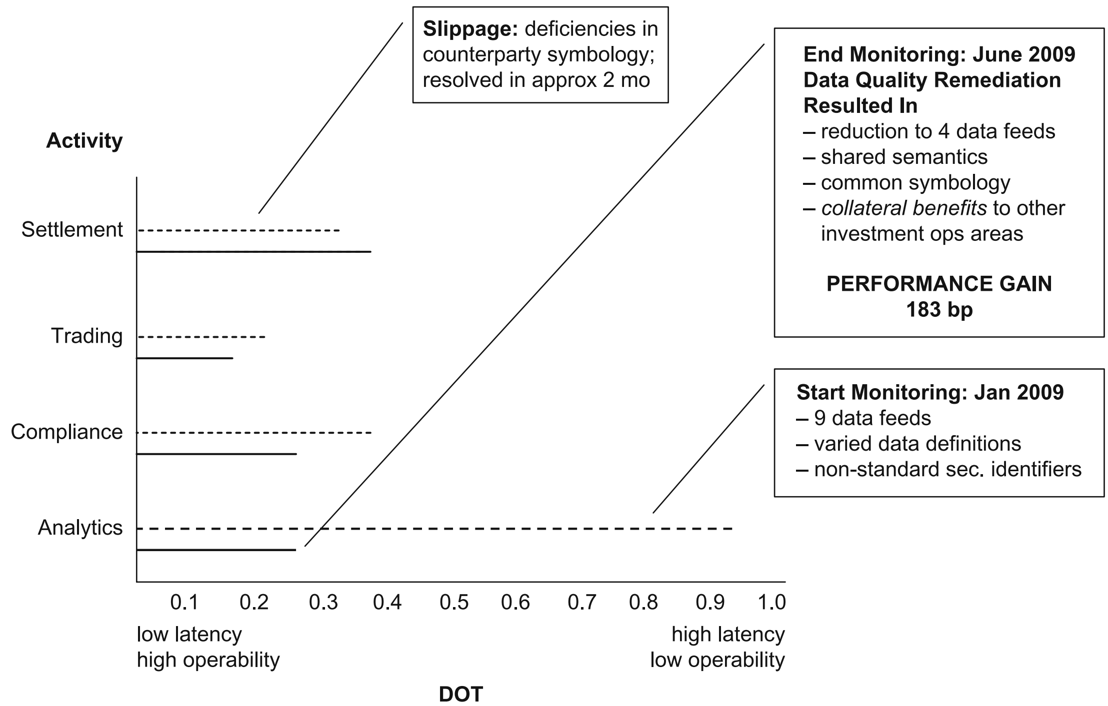
**Aggregate Performance Improvement vs. the Concurrent DOT Values (in bps, relative to the applicable benchmarks, gross of fees)**




cash and equivalents, and swaps) six months after the implementation. The chart shows "before versus after" views of the DOT metrics across each of the four major workflow categories. Note that a reduction in DOT (implying a reduction in the data interoperability burden and, conversely, an improvement in information velocity) in the primary functional domain (i.e., Analytics) also yielded collateral benefits to other functional areas. Note however, the degradation of the DOT metric in the settlements workflow category. This arose from reference data issues that were exposed post-implementation (i.e., historical usage of proprietary counter-party identifiers by fund accounting systems at a custodian resulted in sporadic processing breaks when fed with now industry-standard data from systems upstream).

## EXHIBIT 5

**Example of Observed Performance Improvements for an Asset Allocation Portfolio (in bps and DOT values)**




*Note: Performance relative to the applicable benchmarks, gross of fees. Operational improvement specific to market data usage. See Observation 4 in Exhibit 1 for additional information relating to the example portfolio. Dashed lines indicate pre-remediation DOT state. Solid lines show post-remediation improvements in DOT.*

## DISCUSSION

The quality of a firm's investment operations reflects the sum of its organizational competencies that enable effective translation of investment ideas into expected results. So strategically, the goal of the investment operations function should be to minimize the dissipation of alpha over the forecast duration of the portfolio manager's strategy.

The observations reported in this study provide intriguing indicators of the extent of the investment operation's role in preserving the embedded alpha.[2] These observations point to the importance of efficient investment operations, which can sustain the durability of the portfolio's innate alpha by stemming potential outflows in forecast returns ranging from 51 bps to 242 bps. The dissipation of portfolio performance may stem from outright errors (e.g., incorrect securities symbols; mispricings) and/or opportunity costs associated with information latency (e.g., the inability of the prime broker to reliably communicate securities locates, foreign cash availability, or futures variation margins well ahead of the start-of-day, which then precludes the portfolio manager or trader from timely rebalancing of the order lists prior to the market open).

Additional support for the outcomes in this study can be gleaned by looking at the rate of AuM growth versus performance. We surmise that high rates of asset accumulation are periods when a firm's investment operations become stressed and therefore less efficient. As a result, one should expect to see the firm's performance decay or lag peers during these periods.

Using data from eVestment Alliance, we examined the performance of U.S. large-cap growth equity strategies and U.S. core fixed-income strategies relative to the rate of AuM expansion. We measured the rate of AuM growth over a three-year period from January 2003 to December 2005 inclusive and tracked the one-year returns posted as of December 2005. We selected this observation period since it represents a well-established (low volatility) bull-market characterized by significant fund inflows.

The performance of those managers that had the largest change in assets in the three-year period, and the impact on their performance compared to the median managers for the same period, was insightful. The top decile of firms in terms of AuM growth significantly underperformed the median group by more than 140 bps for equities and more than 40 bps for fixed income relative to one-year returns.

Evidence for the impact of AuM growth on performance also exists in the literature. For example, Christopherson et al. [2002] noted that small-cap managers' excess returns have a statistically significant inverse relationship to annual growth in AuM. Similarly, Xiong et al. [2009] reported that strong inflows adversely affect the subsequent performance of previously top-performing funds.

## LOOKING AHEAD

We would like to re-visit our findings every two to three years with the benefit of an increasingly larger sample set that would ideally consist of more of the same classes of strategies so as to deepen the pool, rather than simply stretch out the span of portfolio types. Our hope is to obtain more precision regarding the performance changes observed, while minimizing statistical errors and biases that may be embedded in our current observations. For example, we have some interesting yet unexplored features in our results, such as performance improvements seemingly bounded within a 50–250 bp envelope or that none of the portfolios that qualified as samples for our study exhibited any degradation in performance relative to the benchmark.[3]

Moreover, we also want to relate our findings more closely to what performance attribution reports convey. In some instances, the attributions we examined did not sum to unity and the excesses were classed under the catch-alls of "idiosyncratic factors" and "other effects." Could, for example, the unexplained residuals be indicative of the information transfer inefficiencies expressed by the DOT metric?

In addition, we also want to evaluate the persistence of the gains from improvements in investment operations. At this stage in our study, we can only surmise that benefits will be diluted over time (at rates unique to each portfolio)[4] since optimal operations is a non-stationary condition. For example, an operations framework that succeeds with the current set of products and clients may become suboptimal with the adoption of new tradable instruments that might better express alpha but are more difficult to manage.

## FINAL REMARKS

The observations and techniques described in this research note have a number of potential applications. For the institutional investor (and their consultants), the approach can be used as a "look-through" tool to

- improve fiduciary oversight (i.e., establish the quality of the manager's investment operations using quantitative measures);
- identify, engage, and retain the better managers (i.e., based on skill plus operational competency); and
- maintain ongoing due diligence (i.e., a methodical process for evaluating their manager's, or candidate manager's, operational soundness).

For the investment manager, our approach offers a number of prescriptive frameworks for

- identifying and isolating inefficiencies in the investment operations;
- laddering the potential portfolio performance improvements contingent on proposed operations initiatives as a way of measuring their potential return on investment (e.g., as a means to more rationally sequence their implementations relative to the availability of people and funding);
- utilizing the DOT metric as a firm-specific input into their risk models; and
- more broadly, improving overall strategy and product performance to better satisfy and retain clients.

# APPENDIX

## DATA OPERABILITY THRESHOLD

DOT (data operability threshold) was first described in Jovellanos [2004] and is a measure of the data mediation "burden" inherent in accurately mapping information between transactions, database records, and other electronic entries (e.g., spreadsheets) to ensure straight-through-processing (STP).

DOT is a message-level metric and is expressed as a dimensionless value between 0 and 1. Zero indicates a significantly low threshold for good data interoperability and so reflects greater efficiencies in information transfer across two or more records. This would typically be exhibited by well-implemented systems interfaces. Conversely, a value close to 1 (i.e., a high threshold) highlights extreme inefficiencies in information transfer and indicates poor data interoperability. This would typically be exhibited in workflows where any form of manual intervention is needed.

DOT is a function of three factors: syntactic gap, semantic gap, and $\Phi$ where

*Syntactic Gap*: arises from differences in the underlying structures of the source and target messages (e.g., usage of specific tags such as <Instrmt> in FIXml versus :35B: in ISO15022 that labels the content of a field as the securities identifier)

*Semantic Gap*: stems from differences in the usage of specific data values in the source and target messages (e.g., a SEDOL code versus the ISIN as the securities identifier)

$\Phi$: a Bayesian component that tracks the recurrence of syntactic and semantic gaps within a data stream, and the conditional probability of a state change from STP to non-STP and vice versa. For example, recent experience within a firm with a particular type of a swap transaction with a counterparty translates into a greater likelihood that a similar swap with another counterparty can also be processed efficiently. Conversely, the first few instances of a new kind of OTC transaction have a higher probability of generating trade errors and processing breaks.

The variables used in our exploratory factor analysis (Henson and Roberts [2006]) were drawn from the outputs of the proprietary tools (i.e., "record shredders"; ontologies) that we used to evaluate the physical structure of the various transactions, database entries, and other electronic records that flow through an asset management firm. The three primary factors that characterize the DOT metric were elucidated from our analysis of factor loadings using 19 underlying variables (see the following table) and varimax (orthogonal) rotation.

| | Variable | Description |
|---|---|---|
| 1 | TYPE | object classified as a Tag, Value, or Record |
| 2 | REG_SPNS_STD | "1" if a published industry standard (0 = "no") |
| 3 | PROP_STD | indicates if a standard proprietary to asset manager (0 = "no") |
| 4 | PRPS_STD | indicates if a widely accepted though proprietary standard (0 = "no") |
| 5 | PROC_TYP | indicates if processing is automated ('1') or manual ('0') |
| 6 | TIME_STD | tenure of standard in months |
| 7 | ELMT_CNT | number of elements in item (including all blanks) |
| 8 | CHAR_SET | character set encoding: complexity weight |
| 9 | TIME_DLT | time (delta) since transaction type last seen |
| 10 | RDF_CNT | number of RDF statements needed to describe object (process) |
| 11 | MFC_CNT | number of MapForce® components needed to map data across records |
| 12 | LEVL_CNT | number of nested levels in Record |
| 13 | OBJ_LEVL_CNT | number of times Tag \| Value repeats across all levels |
| 14 | OBJ_LEVL_LOC | nesting level in which Tag \| Value occurs |
| 15 | RECR_CNT | number of recursions within a level |
| 16 | OBJ_RECR_CNT | number of times Tag \| Value repeats across recursions |
| 17 | OBJ_RECR_LOC | recursion level in which Tag \| Value occurs |
| 18 | SND_CPTY_RNK | counterparty historical ranking: data operability for Record type |
| 19 | RCV_CPTY_RNK | counterparty historical ranking: data operability for Record type |

## ENDNOTES

[1]Ontologies represent rigorously structured and curated descriptions of objects and processes (e.g., a "condor" as a trade strategy and its use of multiple options). Our proprietary ontologies were implemented using standard RDF statements within an OWL-Full framework per W3C [2010]. We have found that technologies developed for the "semantic web" are better suited to evaluating and handling securities transactions since many of these electronic messages are, in practice, complex documents. For example, a corporate actions notice for a ReOrg event contains a significant amount of free-form information, despite the heroic efforts expended by ISO, SWIFT, and various industry working groups in promoting messaging standards, rigorous transaction structures, and industry-wide best practices. As most practitioners are aware, ensuring the fidelity of such complex corporate action events across different transaction types and systems (e.g., in support of pre-trade compliance checks) is fraught with potential risk.

[2]To date, the interplay of investment operations and alpha has been explored mainly in the service marketing domain under the catch-phrase of "Operational Alpha." See, for example http://www.omnium.com (formerly Citadel Solutions), or http://allaboutalpha.com/blog/2007/06/20/operational-alpha/. "Operational Alpha" has a satisfying veneer to it given its simplicity to state, and its intuitive interest and value as a thought-leadership slogan. However, it is fraught with imprecision (e.g., it implies operations actually generate alpha). Moreover, the service providers' discussions on their websites provide no empirical support for the casual assertion that operations is in fact a native source of alpha.

[3]Preliminary examination of those portfolios that did *not* qualify for this study (i.e., two or more operational updates were being applied concurrently, such as "implement automated broker matching" coupled with "automate trade date reconciliation with prime brokers"), showed that 11 of those portfolios exhibited declines in performance relative to their respective benchmarks (gross of fees). For now, intuition suggests that multiple operational initiatives may have diluted performance down, in the same vein that rapid AuM growth stresses investment operations, which then run less efficiently.

[4]Interestingly, in our analysis of large-cap growth equity strategies and core fixed-income products described in this article, differences in the two- and three-year returns between the top and median decile of managers (ranked relative to the rate of AuM growth) were no longer statistically significant.

## REFERENCES

Christopherson, J.A., Z. Ding, and P. Greenwood. "The Perils of Success." *The Journal of Portfolio Management*, Vol. 28, No. 2 (2002), pp. 41-53.

Coppejans, M., and A. Madhavan. "The Value of Transaction Cost Forecasts: Another Source of Alpha." *Journal of Investment Management*, Vol. 5, No. 1 (2007), pp. 65-78.

Henson, R.K., and J. Roberts. "Use of Exploratory Factor Analysis in Published Research: Common Errors and Some Comment on Improved Practice." *Educational and Psychological Measurement*, Vol. 66, No. 3 (2006), pp. 393-416.

Jovellanos, C. "ContextMetrics™: Semantic and Syntactic Interoperability in Cross-Border Trading Systems." 20th International Conference on Data Engineering, ICDE '04, April 2004, pp. 808-810.

Obizhaeva, A.A. "Information vs. Liquidity: Evidence from Portfolio Transition Trades." EFA 2007 Ljubljana Meetings Paper, January 8, 2007.

Perold, A.F. "The Implementation Shortfall: Paper versus Reality." *The Journal of Portfolio Management*, Vol. 14, No. 1 (1988), pp. 4-9.

W3C. "Resource Description Framework (RDF)." World Wide Web Consortium, 2010: http://www.w3.org/RDF/

Xiong, J., T.M. Idzorek, P. Chen, and R.G. Ibbotson. "Impact of Size and Flows on Performance for Funds of Hedge Funds." *The Journal of Portfolio Management*, Vol. 35, No. 2 (2009), pp. 118-130.