Improving Investment Operations through Data Science:

A Case Study of Innovation in Valuation

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Abstract: New technologies in data science are allowing long-term investors to bring much more rigor to their operations. This paper thus shows empirical examples in support of the data-driven advances, demonstrating their practical applications. We use the UC Investments office as our case study, and we discuss how adoption of advanced data science techniques can move organizations past the current unsatisfactory state of the art, to an unprecedented level of operational finesse. Specifically, we focus on a methodological innovation in fair valuation of illiquid assets that is supported by an automated, rigorous process. We test this process in a real-world setting, and find, at least in this case, that these advances can enhance roll forward outputs in terms of timeliness, accuracy and granularity. This has several potential impacts, not only for reporting, but also for investment, risk management, actuarial purposes and even personal compensation of teams.

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Introduction

This paper introduces a methodological innovation in fair value measurement of illiquid assets that addresses limitations in current practices, and extends the usefulness of fair value quantities for limited partner (LP) organizations. However, the true purpose of this paper – which is perhaps better described as an in-depth case study – is broader than any single data science tool or application. We wrote this paper and are sharing this case to help explain the value of bringing sophisticated data science tools inside a pension fund, endowment, or other long-term investment organization. Ultimately, we believe that new technologies in data science will allow long-term investors to bring much more rigor to their operations, which would be universally positive for the community of asset owner investors.

Our case study is focused entirely on UC Investments[1], the managing entity for the University of California's various investment products, including its endowment, pension, retirement savings plan, and working capital. At the time of writing, UC Investments had $118B in assets under management, of which approximately 9% comprised illiquid assets (UC Investments, 2017). As with many of its peer investment organizations, technology was under-developed compared to what one might expect from private industry. As such, the organization could see incredible improvements thanks to small changes, which is ultimately what this case study shows.

In what follows, we introduce our case study of UC Investments' fair value conundrum. While the below at times goes into some technological detail on what may appear to be a niche investment topic, we offer this level of detail to highlight the utility and relevance of data science in the context of investment operations and the challenges that need to be overcome. Specifically, we focus on a methodological innovation in fair valuation of illiquid assets that is supported by an automated, rigorous process. We test this process in a real-world setting, and find, at least in this case, that these advances can enhance roll forward outputs in terms of timeliness, accuracy and granularity. This has several potential impacts, not only for reporting, but also for investment, risk management, actuarial purposes and even personal compensation of teams.

Case Study: The Fair Value Conundrum

In this case study, we focus on the issue of financial reporting, which is a key fiduciary requirement for institutional investment organizations. The natural centerpiece of such reporting tends to be current portfolio values. Fair value[2] now routinely replaces alternative accounting approaches (Ryan, 2008) of illiquid

[1] UC Investments is the Regents of the University of California's Office of the President, Office of the Chief Investment Officer.
[2] There is general agreement among the various standards and industry groups as to the definition of fair value: *the hypothetical price that would be received to sell an asset in an orderly transaction at the date of measurement.* International Financial Reporting

assets, thereby providing stakeholders with – at least notionally – a unified, synchronous view of whole portfolio performance. As allocations to illiquid classes increase, however, the reliability of fair value is increasingly important to other areas of the LP organization, including investments, risk, operations, and actuarial processes. Paradoxically, the subjectivity of fair value – intended to enhance investor understanding – causes it to be unreliable. The literature finds that asset managers (GPs) (mis)use the subjectivity of fair value to boost performance at fundraising, smooth returns, and influence investor expectations (Barber and Yasuda, 2016; Czasonis, Kritzman and Turkington, 2017; Jenkinson, Sousa and Stucke, 2013) even though these valuations are typically produced by independent valuation experts[3]. At the scale of the LP portfolio, which may contain holdings in thousands of private companies, two interrelated problems arise from this practice. First, bias in the 'base case' estimate (i.e. fair value of the individual company within a fund) results in an unreliable portfolio value[4]. Second, the additional disclosures required to substantiate subjective fair value company estimates cause fund reporting to be lagged, typically by months and sometimes quarters.

It is within this opaque and complex environment that many LPs are asked by their sponsors and stakeholders to report fair value, and do so objectively and ahead of their asset managers. The difficulty of this challenge has led LP auditors to accept a modified form of fair value estimation as a pragmatic necessity to their reporting constraints. In accordance with fundamental financial reporting concepts, specifically *relevance* and *faithful representation* (FASB, 2010), the LP via a procedure known as a "roll forward" may estimate fair value. The roll forward procedure takes the most recently reported GP-estimate of fair value and adjusts it to account for the intervening period. The resulting calculated fair value sidesteps the need for a ground-up appraisal (the base case), and achieves the desired reporting timeliness.

However, along with timeliness is *usefulness*, and in this dimension the roll forward falls short of its potential. As in all manual procedures, there is a direct trade-off between cost and quality. In the case of a roll forward, modern quality-oriented activities, such as back testing against prior periods, are typically foregone. Resistance to such budget allocation is warranted because quality gains can't necessarily be leveraged: an investment in back testing this year may not result in a better roll forward next year. The consequence of

Standards 13: Fair Value Measurement; Financial Accounting Standards Board Statement 157 / ASC Topic 820: Fair Value Measurement; U.S. Government Accounting Standards Board Statement 72: Fair Value Measurement, Disclosures; International Private Equity & Venture Capital (IPEV) Valuation Guidelines 12/2015 ed.

[3] According to the (formerly named) Financial Services Authority (FSA Discussion Paper 06/06), private equity firms number among the largest clients for most big financial intermediaries – banks, lawyers, accountants, management consultants – creating the potential for moral hazard. In particular, the revenue stream a service provider receives from a private equity firm "may cause them to consider actions that they would normally discount" (Section 4.61). For example, one (unnamed) bank earned almost 900 million euros from its private equity-related activities in a year, while another bank was shown to generate over 50 percent of its income from private equity.

[4] Research demonstrates that base case valuation bias varies predictably according to: i) the quarter being reported, where year-end valuation bias is predominantly positive (Czasonis, Kritzman, and Turkington, 2017); and ii) the maturity of the fund, where later stage valuation bias is predominantly negative (Jenkinson, Souza, and Stucke, 2013).

this lack of rigor is that the conventional roll forward produces quantities that satisfy a one-off reporting exercise, but which are otherwise orphaned. This is evidenced generally by the infrequency[5] of the procedure, and specifically by the failure of other LP functions, e.g. risk processes, to source critical inputs from it.

Although the roll forward procedure is used specifically to predict forthcoming GP-estimates of asset values, statistical techniques to measure or enhance its predictive accuracy are rarely, if ever, employed. The procedure is normally executed by personnel entering values into spreadsheets, and demands no testing of parameters, assumptions, or outcomes. Instead, practitioners use coarse, 'one-off' corrective methods such as thresholds to control the impact of methodological assumptions on portfolio value. As a simple illustration, consider the application of a ten percent reporting hurdle at the fund level. If the roll forward estimate of a single fund is less than ten percent different from its previously reported fair value, a coarse but seemingly reasonable corrective mechanism might simply report zero value change. However, if a larger portion of funds is off in the same direction, then the valuation of the portfolio is materially impacted.

In this case study, we highlight how a statistical approach to the roll forward where the behavior of the outputs as a group – the shape of the distribution, size of residuals, and accuracy of underlying methodologies – is explicitly captured. These quantities form a performance baseline against which the impact of methodological enhancements, better data, and even the GP-specific biases described previously can be observed. Deviations from expected outcomes, even at the asset level, may be flagged for examination.

Since discovery and methodological enhancement require systematic testing against the performance baseline, an automated test harness – and therefore an automated roll forward – becomes a practical necessity. Offering repeatability and efficiency, automation also provides a natural extension to the power of a statistical approach. Combined, automation and statistical methods can dramatically accelerate development while minimizing variability arising from human error and theoretical deficiencies.

However, successful automation of the roll forward ultimately depends upon the quality and availability of input data, a not insignificant challenge facing LP organizations everywhere. In consideration of this fact, the automation study described herein specifically defines and uses 'real-world' data[6] and commercially available tools[7]. This indicates that automation is indeed within reach of 'typical' LPs in terms of data readiness.

[5] Roll forward procedures are typically run annually for external reporting purposes.
[6] In this case, 'real-world' refers to the current operations of UC Investments' illiquid assets portfolios, and is an acknowledgement of the incompleteness and non-uniformity of GP-provided reporting data faced by most if not all LPs.
[7] The tools used in this study are proprietary to FEV Analytics, the Chief Data Scientist of which is a co-author of this paper.

We also hope that our choice of case study shows that other implementation realities, such as demands on budgets, systems, and personnel, do not prevent most LPs from modernizing. In fact, our approach illustrates that even far-reaching innovations can 'start small' and quickly add value. For instance, a roll forward procedure that is an annual event, with personnel requirements in the vicinity of 250 hours, is far from the largest line item in an operating budget. It may nonetheless be wasteful because very little – if any – of the resources required to collect data and produce the roll forward is reusable[8]. In contrast, the automated roll forward requires similar resource consumption to implement, but offers far greater capacity to amortize effort and reduce operating costs.

Automation also unveils value in unexpected places. The procedure demonstrates turn-around time of less than a day, with improved accuracy and reliability compared to the manual approach. Together these qualities make the roll forward procedure much more useful, beyond operations, because they dismantle long-standing structural barriers like reporting lag. In fact, to the extent permitted by the LP's 'data conviction'[9] and adoption of data science technology, other fundamental limitations, like subjective valuations, can be mitigated. In this way, the roll forward can be developed to produce an expanded set of outputs, informing a broader set of monitoring functions on a frequent and/or as-needed basis.

The Incumbent Roll Forward Procedure

The conventional roll forward comprises three components that are additive: a starting value; a cash flow adjustment; and, a market adjustment. The conventional procedure can be described as:

$$\textit{Roll Forward Estimate} = \textit{Starting Value} + \textit{Cash Flow Adjustment} + \textit{Market Adjustment}$$

where both the cash flow adjustment and the market adjustment may be positive or negative.

Starting Value

The most recent net asset value (NAV) of each fund as reported by the GP is used as the starting value.

Cash Flow Adjustment

The cash flow adjustment methodology subtracts fund inflows and adds outflows for the period. Appropriate categorization of cash flows avoids erroneous deduction of operating quantities – e.g. ordinary income or management fees – from the fair value of the fund's assets. Ideally, cash flows are individually dated rather

[8] For instance, in the space of even a quarter, data and the relationships between the data will have changed, requiring the framework to be modified. If the framework is a spreadsheet template, then updation is essentially a line by line manual process.
[9] 'Data conviction' refers to the LP's willingness to demand, collect and operationalize its investment data.

than clumped, and tracked against their respective assets rather than netted to the level of the fund. If the data does not tie cash flows and dates to assets, then the methodology necessarily degrades. For instance, fund level cash flows may be apportioned to component assets thoughtfully using a weighting mechanism, or simplistically using an even split.

Market Adjustment

The market adjustment methodology is a two-step process, beginning with a proxy value ratio applied to the previous period value, as per:

$$(1) \qquad Asset\ Value_{Previous\ Period} \times \frac{Proxy\ Value_{Current\ Period}}{Proxy\ Value_{Previous\ Period}}$$

The proxy value varies according to the type and sub-industry of the security being estimated, for example an industry benchmark for a buyout versus a futures pricing model for an energy asset. If sub-industry data is unavailable, then the methodology adjusts to a more general or proxy value.

The next step weights the contribution of each intra-period cash flow according to time remaining in the period. For instance, if an asset were acquired ten days after the start of the period, then the weighting would be 80/90 or 0.89. This ensures that market adjustments applied are appropriate. Where asset cash flows are not tied to dates, an assumption is forced as to the timing – for example, to the middle of the period where the weighting would be 0.5.

$$(2) \qquad \frac{Days\ Remaining_{Current\ Period}}{Total\ Days_{Current\ Period}}$$

The market adjustment is then a matter of multiplying (1) and (2).

The roll forward output is the summed starting value, cash flow adjustment, and market adjustment.

Data Requirements

The completeness of the reporting data available to the procedure is plainly consequential to the methodology, and to the accuracy of the output. In this paper we consider data 'completeness' primarily in terms of its granularity. To help frame data granularity, Exhibit 1 depicts three 'classes' of GP-reported data, increasing in granularity from left to right.

Exhibit 1: Schema for Classifying Input Data

	Basic **Class 1**	**Better** **Class 2**	**Best** **Class 3 [A]**
Specific to LP	**Cash Flow Quantities** Currency Fee/Non-fee classification **Holdings Quantities** Fund NAV	**Cash Flow Quantities** *Basic +* Asset-specific Date-specific Descriptive apportionment [B] **Holdings Quantities** *Basic +* % equity in fund	**Cash Flow Quantities** *Same as Better* **Holdings Quantities** *Same as Better*
General to Fund	**Cash Flow Quantities** **Holdings Quantities** Schedule of Investments Public/Private Industry, Geography Date of Entry Fund NAV **Asset Performance Quantities**	**Cash Flow Quantities** Currency Fee/Non-fee classification Asset-specific Date-specific Descriptive apportionment [B] **Holdings Quantities** *Basic +* Sub-industry [C] Date of Exit Ownership % **Asset Performance Quantities** Asset NAV	**Cash Flow Quantities** *Same as Better* **Holdings Quantities** *Same as Better* **Asset Performance Quantities** *Better +* Entry EV / Exit EV Revs (entry, quarterly TTM, exit) EBITDA (entry, quarterly TTM, exit) Total Debt (entry, quarterly TTM, exit)
Source	P-CAP Statements Quarterly Reports Quarterly Cash Flow Report	*Basic +* ILPA templates [D]	*Better +* Entry reporting [E]
Notes	[A] Class 3 quantities are routinely prepared by GPs and do not add burden to reporting requirements. For example, asset performance quantities are standard in fundraising materials. [B] Examples of cash flow descriptions include 'capital call', 'capital gains', 'return of capital', 'ordinary income', etc. [C] Sub-industry precision affects the market adjustment; for example, the proxy value for an upstream oil and gas asset differs substantially from that of a midstream oil and gas asset. [D] The Institutional Limited Partner Association has published reporting templates for fees and cash flows. At the end of 2017, more than 200 general partner entities are completing the template when asked (ilpa.org). [E] Entry reporting describes the price of the asset at entry, total debt, deal team, etc. and can be sourced from different documents. While these data are found in quarterly reports, they are normally provided in narrative form. Documentation for subsequent fundraising usually provides these same data in more useful spreadsheet format.		

As the schema depicts, and as supported in the literature (Braun, Jenkinson and Stoff, 2015), it is component company data that enables the implementation of more reliable methodologies. Fund-level NAVs and cash flows netted (to the fund and to the period) create ambiguity when aggregated (see, for example, Harris et al, 2014). In the roll forward procedure, they are similarly limiting. For instance, the reliability of the cash flow adjustment is immediately enhanced if the cash flows are tied to their respective underlying holdings rather than aggregated to the fund level. As expected, cash flows tied to dates allow for more precise market adjustments. Consider the following example:

Fund A holds 10 assets, of which the LP's total interest is approximately $50M. During the roll forward period, *Asset 1* is sold at a 21% gain on its previous period mark (starting value). Its distribution to the LP is approximately $15M. However, the intra-period data does not tie the distribution to *Asset 1*. As a result, the cash flow adjustment subtracts $15M from the $50M, apportioned across all 10 assets, and without accounting for the intra-period 21% gain on *Asset 1*. This leaves the cash flow adjusted value approximately $3M below where it should be. During the roll forward period, the benchmark of *Asset 1* experienced a material reduction, while other fund asset benchmarks experienced appreciation. As a further consequence of incomplete data, the assumed apportionment amplified the negative contribution of *Asset 1*'s benchmark, reducing the market adjustment by approximately $2.3M. Other factors contributed to further mis-estimation. In total, the roll forward of *Fund A*, a $50M holding for the LP, misses its estimated mark by approximately $8M.

The schema shown in Exhibit 1 emphasizes the need for the roll forward procedure to identify and adjust to different classes of reporting data between funds across the portfolio, fully exercising more granular data where available. It also acknowledges that, for an innovative approach to be generalizable, it must not impose a data requirement in excess of what is typical in the industry. Hence, Class 1 data represents the norm of LP-accessible data today, while Class 2 data is largely satisfied by data captured within standardized reporting templates, such as those provided by the Institutional Limited Partner Association (ILPA, 2018).

Towards Class 3 Datasets

Class 3 data is defined by the addition of each fund's component firm entry price and operating values at entry and interim. These data are germane to intelligent market calibration throughout the holding period, which in turn adds value to the roll forward procedure. As indicated in Exhibit 1, these data may typically be sourced from quarterly and annual reports, cash flow notices (ILPA template), as well as [subsequent] fund raising materials. Therefore, graduating data sets from Class 2 to Class 3, even on older funds, should not be burdensome.

Anecdotally, the greater challenge for the majority of LPs lies in the construction of a Class 2 data set. The volume of investment data to achieve Class 2 compliance can quickly overwhelm even LPs with large internal staffs (Brandmeyer and Kojima, 2015). Absent a way to exercise the data, LPs are without a sufficiently compelling reason to allocate necessary resources. This is where data science technology has changed the conditions; the relatively staggering resource efficiency of data science technology can 'afford' to make measurement of a fund's component firms – Class 2 and 3 data – its logical focus. As data science technology accelerates applications for private assets, LPs with incomplete Class 1 data sets will find themselves with higher operating costs and greater information asymmetry than their peers. It is our intent that by sharing the input data schema, LPs can advance their data readiness and technology adoption.

Our emphasis on asset level data is in contrast to some calls for GPs to increase reporting artifacts with, for example, value bridges. Unfortunately, these metrics are theoretically deficient (Porter, forthcoming 2018) and offer no value to the LP. A better approach, that cuts down subjectivity and ingestion challenges, is to seek Class 3 data in basic data formats[10]. At UC Investments, data conviction is a top-down mandate that publicly declares a preparedness to 'walk away' from partnerships that don't provide data. Within the investment organization, the Chief Investment Officer emphasizes nurturing a man-machine symbiosis (UC Investments, 2016) which includes resources for the construction of data sets and data systems. While such an assertive posture may be unusual amongst LPs, UC Investments has nonetheless cultivated cooperation from its partners, and Class 2 datasets are underway over most alternatives funds.

Study 1: Feasibility of Roll Forward Automation (restricted to Class 1 data inputs)

The first case study at UC Investments was to implement a statistical approach and assess the feasibility of automating the roll forward procedure. To advance generalizability of the results, the *least* optimal data conditions were simulated: inputs were restricted to Class 1 data from a single preceding time period. The solution was then run on more than 300 funds at UC Investments across a range of assets (Buyout, VC, Real Assets, and Real Estate) and the outputs compared to actuals.

Automation is defined as a technology solution capable of completing the roll forward in short time frames, i.e. one day or less for the entire alternatives portfolio, and consisting of the following procedural components:

- A **data ingestion** process capable of handling non-standard and multi-format raw data from various sources.
- A **data framework** specific to UC Investments.
- Codified management of the roll forward process (**roll forward method**).
- **Component methodologies** coded and performance tested.

[10] It is observed that data is often supplied by GPs in formats and narratives that, generally, make ingestion to data systems difficult. We specifically call out the conversion of tabular data and spreadsheets to PDF as needlessly burdensome to the LP.

- **Quality assurance**, comprising i) flagging of erroneous input data; ii) regular exercise of UC Investments' data; and iii) a continuous improvement framework.

The solution as described represents significant effort, the underlying economics of which do not readily support a single implementation at UC Investments. UC Investments therefore collaborated with an independent data science firm to construct the solution as a customization to their proprietary measurement platform. On an ongoing basis, the automated roll forward is implemented as a turn-key service requiring no additional investment by UC Investments in specialized systems, personnel, or data service providers. It is also expected that due to automation, future demands on the time of internal resources will decrease.

Data Ingestion

Data ingestion is considered as having two phases. The first phase is the initial mapping of the data that enables the construction of a data framework, described below. The second phase happens on a 'per run' basis and is regularly varying as GP-reports are received.

In the first ingestion phase, data and data sources are examined for their identity and relationships. With private asset data, this is an unavoidably inelegant process due to the non-uniformity of the data. As a simple illustration, a single fund may be identified alphanumerically (i.e. CUSIP), or a friendly name (e.g. Capital Partners IV), or a legal name (Capital Partners IV-A LLC), depending on the data source (e.g. accounting, custodial, operations). In the case of an asset inside a fund, the business may have a legal name (e.g. Tech Holdco), a friendly name (e.g. General Tech), a dba name (e.g. Edu-Tech) – and all three may change during the holding period. Identity is further encumbered by syntax and entry errors. The first step is to create unifying identities and the second is tie out data accurately. On this basis the data framework may be constructed (see following section).

Within the data framework, the second ingestion phase assembles inputs appropriately on a per run basis. Configuration includes applying run-specific parameters (e.g. date), special instructions (e.g. GP-specific 'rules'), and completing modifications to the data framework as required by the inputs (e.g. when a fund has a new asset).

Data Framework

The data framework codifies the many data identities and the relationships between them over time. At a high level, this ties together data between the Investor and the Investment (see Exhibit 2) and ensures quantities are traceable. While 'core' identities, such as fund name, are relatively static over time, other identities, such as asset name, are less static as investments are entered and exited. The framework was therefore designed to detect the need for modification as part of the roll forward procedure (described below), and update automatically.

Exhibit 2: Conceptualizing the Data Framework

	Investor		Investment	
	Beneficiary	**LP**	**Fund**	**Asset**
Example Data Classes & Sub-Classes	**Funds** Endowment, Pension, etc. **Defined Pools** Products, Campus, etc.	**Asset Portfolios** Alternatives PE, Real Assets, etc. **Strategy** Growth, Co-invests, etc.	**Structures** Funds, Vehicles, etc.	**Securities** Equity, Debt, Off-Takes, etc.

The complexity of the requirements, and the non-standard state of the data in general, makes codifying the data framework a non-trivial exercise in terms of effort and expertise. In our experience, this step benefited from collaboration between data scientists and in-house operations personnel to ensure appropriate access to data and clarification as needed.

Roll Forward (Automated Method)

Exhibit 3: Processes in the Automated Roll Forward

	Process	Activities	Quality Assurance
1	Setup	Locate and identify inputs Run-specific configuration	"Sanity checks" are embedded in the code for processes 1-3.
2	Input	Ingest data Update data structures	
3	Prepare	Check data class, 'hold' or 'retreat' component methodologies Check data expectation, set up fallbacks [A] Create benchmarks / get stock prices Create roll forward matrix	
4	Perform	Execute roll forward procedure Handle failures by reverting to fallbacks	Flagging of large or unexpected changes
5	Output	Aggregation as necessary Produce output files	Analysis of residuals (performed after GP-reports have been received)
		[A] e.g. *"I was expecting a stock ticker and didn't find one"*. Fallbacks are a set of instructions, sequenced best to worst alternative, to handle missed data expectations.	

The automated method manages the execution of all procedural components – ingestion, framework modification, methodologies – to complete each roll forward procedure, or 'run', to the accepted quality standards. The method contains five processes, with quality assurance process embedded in each, an overview of which is described in Exhibit 3.

Component Methodologies

The component methodologies – the cash flow adjustment and the market adjustment – are applied by the automated roll forward method according to the completeness of the asset's corresponding inputs, i.e. Class 1, or Class 2, or Class 3 data. This graduated series of methodologies allows each roll forward run to make use of best available data, including directly observable price when available, in accordance with fair value hierarchy (FAS 157).

Perhaps the most challenging aspect of the automated solution is the market adjustment component. Market adjustment is usually inferred by mapping the growth of a public benchmark onto the private asset, making benchmark selection germane to the output. However, the subjectivity of benchmark choice is detrimental to the technical integrity of an automated solution, which demands objectivity.

Ordinarily, maintaining objectivity would force an automated market adjustment to become generalized (i.e. one benchmark for all assets), sacrificing accuracy. To achieve both objectivity and accuracy therefore necessitates a significant methodological enhancement, achieved in this case by modern proxy benchmarks[11] (Porter and Porter, 2017), a data science technology.

Extensive testing was conducted on five market adjustment methodologies, of which three were selected as promising roll forward methodology candidates. These were compared to actual returns by correlation, bias and error. Within the data constraints, methodologies utilizing modern proxy benchmarks returned the highest correlation (see Exhibit 4), and did not introduce any manual or subjective component to the market adjustment methodology.

The results shown in Exhibit 4 formed the basis of a structured automatic 'retreat' by the market adjustment methodology, from most specific benchmark to least specific benchmark, in response to the availability of input data on each component company within a fund.

[11] Modern proxy benchmarks are state-of-the-art, non-market-cap-weighted indexes, carrying 50-150 public constituents and constructed systematically on the basis of technical similarity and stability. They are fully investible and managed as a virtual synthetic investment that precisely mirrors the changing nature of the private asset over time.

Exhibit 4: Accuracy of Market Adjustment Methodologies
Tested Against 2.4 Million Randomly Chosen Portfolios Between 1/1/2000 and 5/1/2017

Measures	Methodology 1: Most Specific [A]	Methodology 2 [A]	Methodology 3: Least Specific [B]
Correlation [C]	0.6868	0.6454	0.4139
Bias [D]	0.0058	0.0062	-0.0009
Absolute Error [D]	0.0349	0.0364	0.0350

[A] *Methodologies 1 & 2 utilize modern proxy benchmarks*[11] *rather than a broad benchmark. Methodology 2 relies on basic asset-level data, such as industry and starting value, a sub-set of the input data utilized by Methodology 1.*

[B] *Methodology 3 utilized the Russell 3000 index uniformly as the basis of market adjustment.*

[C] *Median correlation was highest for methodologies that used benchmarks more specific to asset size and industry.*

[D] *Results shown are for portfolio sizes of 500 assets, and describe results from three time-periods designed to capture differing volatility, i.e. dotcom bubble and correction, mortgage bubble and credit crisis, and relative economic stability.*

Quality Assurance

Quality assurance is intertwined throughout components and stages of the roll forward procedure. We discuss here two aspects of quality assurance: data exercise and continuous improvement.

Given the non-uniformity of private investment data, regular cross-checking is imperative to surface errors. For instance, portions of the data come from multiple sources, i.e. custodial source, accounting source, reporting source, operations source, etc. These sources may compile different representations of the same data that are difficult to compare without the context provided by the data framework. Systematic exercise therefore refers to Steps 1 – 3 of the Roll Forward Process (see Exhibit 3), and allows discordant/suspect quantities to be surfaced and pursued in much the same vein as a software bug is surfaced and fixed.

Lagged GP-reporting and varying cash flows typically means that new data 'dribbles in' over time. Against this backdrop, automation exerts no incremental cost to regular exercise of the data, even when done daily. The result is that at no time is there a significant build-up of error probability, and operations data becomes increasingly reliable. As experienced at UC Investments, this has benefited processes other than the roll forward, and simultaneously contributed to more effective management of the various data sources.

Continuous improvement encompasses all aspects of the procedure, including data ingestion, but is outcome focused as measured by improved statistical performance[12]. Statistical performance can be improved by resolving structural limitations, such as stale starting values, and it can be improved by methodological enhancements. As data quality moves towards Class 3 compliance, methodological enhancements will obviously have greater impact on performance. It should be noted that methodologies used in a conventional

[12] Other performance criteria such as total production efficiency and usability also form part of the continuous improvement program but are not discussed in this whitepaper.

roll forward procedure do not measure appropriateness of benchmarks, handle precise timing of cash flows, or in any way flag stale starting values. However, without automation, the time and effort required to engage in continuous improvement meaningfully is simply cost prohibitive. Additionally, without the test harness, the rigorous testing needed for a statistical understanding of the output and its expected error distribution is less reliable and (again) cost prohibitive. For instance, in our case study we used millions of simulations over many time periods to enhance the market adjustment methodology. This would have been impractical to do without an [automated] test harness.

Results of Study 1 (Feasibility of Roll Forward Automation)

The roll forward outputs of the fully automated procedure and the incumbent procedure were compared for overall accuracy to GP-reported NAVs. As shown in Exhibit 5, the manual and automated procedures produce results that are not significantly different (21 basis points). This is a meaningful result given that the incumbent procedure benefited from unrestricted access to data from multiple previous time periods.

Exhibit 5: Comparison of Roll Forward Procedures for Overall Accuracy of Estimations to GP NAVs.

	Manual (Incumbent) Procedure	**Fully Automated Procedure**
Accuracy (% difference to GP-reported NAV)	-1.52%	-1.73%

When considered in terms of time and effort, the automated procedure is immediately efficacious to portfolio operations. The time to produce the roll forward estimate on the entire portfolio is reliably less than 24 hours, and can be run as needed. Importantly, the automated procedure and its subsequent improvements can be managed to modern quality assurance standards.

Study 2: What Performance Improvements Can Automation Unlock?

With feasibility of automation established, a representative subset of investments was created for further analysis. The subset consisted of 70 investments summing to approximately 60% of the total alternatives portfolio value, with each of the portfolio's sub-classes represented.

Results from the automated procedure were analyzed first for origin or cause of difference, then grouped according to the component where the difference occurred (see Exhibit 6). This provided quick insight as to where methodological enhancement could quickly improve accuracy. For example, applying standard data cleaning processes to input data (not applicable in the automation analysis due to imposed data access restrictions) could substantively improve performance.

The most straightforward enhancement pertained to the data included in the cash flow adjustment. Cash flow attribution is usually available in data format from GPs, often forming part of the standard data provided in an inception-to-date commitment schedule. As indicated in Exhibit 6, the assets where inclusion of cash flow attribution had the most impact on roll forward accuracy was Real Estate.

The analysis revealed multiple avenues for methodological enhancement to the market adjustment component beyond the use of proxy benchmarks. The most broadly applicable enhancements modeled relevant futures contracts (in the case of real assets), and alternate markers for property appreciation (e.g. trailing averages in the case of large perpetual real estate funds).

Exhibit 6: Difference Analysis of the Automated Procedure

Difference	**Prevalence (% Assets)**	**Contribution to Absolute Difference (%)**	**Class Impact** [B]	**Illustrative Example**
Input data [A]	14.0%	20.8%	All	Wrong date of starting value caused a 15-month market adjustment instead of a 3-month market adjustment.
Cash adjustment	7.0%	6.0%	Real Estate	Estimated pending distributions not included in roll forward NAV.
Market adjustment	14.0%	11.0%	Real Assets	Market adjustment of upstream energy asset benefited from modeling futures contracts instead of proxy benchmarks.
Starting value	2.8%[C]	17.5%	Co-investment	Revaluation of the asset during the period at a significant premium to starting NAV.

[A] The imposed data restrictions limited the potential for and scope of data cleaning – a normal element of the ingestion process. Input data that fell out of expected range would normally trigger inspection. However, with no alternate data (quarterly reports etc.) to access, basic cross-checking and cleaning could not be conducted.

[B] While all types were found in all asset sub-classes, some differences had a disproportionate impact on certain asset types.

[C] It is thought that the prevalence is much larger, but detection by the technology in the absence of a revaluation requires access to a larger data set.

Results of Study 2 (Data and Methodological Improvements)

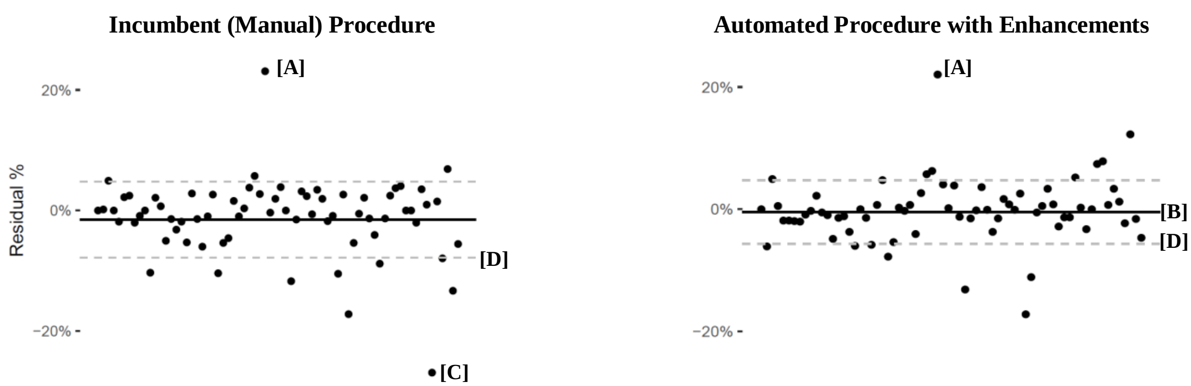
The automated procedure with imposed data restrictions showed similar difference (-1.73%) to the GP-reported values as the manual procedure (-1.52%), whereas the automated procedure with enhancements (-0.46%) was much closer to the eventual GP-reported values than either the manual procedure or the first run automated procedure (see Exhibit 7). While implemented enhancements affected only a third of the subset investments, accuracy was significantly improved.

Exhibit 7: Accuracy of Automated Procedure with Enhancements

	Manual Procedure (Incumbent)	Automated Procedure with Imposed Data Restrictions (Study 1)	Automated Procedure with Improvements (Study 2)
Accuracy (Median % difference to GP-reported NAV)	-1.52%	-1.73%	-0.46%

The results were further analyzed for median absolute percent difference (MAPD) to understand the statistical spread of the results (depicted graphically in Exhibit 8). The narrower standard deviation error bands of the enhanced procedure mean that the overall result is more accurate for the automated procedure with enhancements, and that the difference attributable to any one investment is reduced.

Exhibit 8: Comparison of Results



[A] The largest holding in this fund had an IPO during the roll forward period at a valuation 41% less than estimated by the GP in the previous quarter.
[B] The median accuracy of the automated procedure (solid line) was -0.46% less than the GP-reported values, a two-thirds reduction in bias over the incumbent procedure.
[C] This outlier in terms of % difference also carried a significant investment exposure that (alone) triggered materiality thresholds.
[D] The standard deviation or error bands (broken gray lines), show a concentration of the results around the median, i.e. the results are more reliably accurate.

Limitations of the Roll Forward Procedure

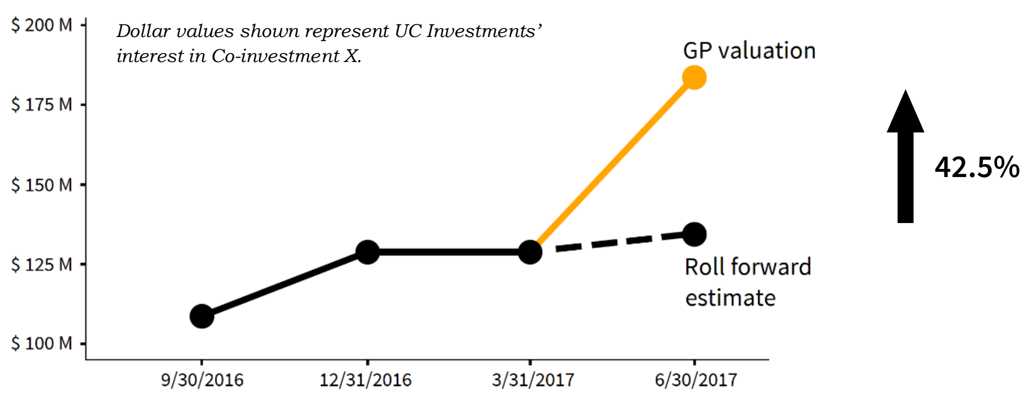
The most impactful limitation of the conventional roll forward procedure is its reliance on an unverified starting value. If the starting value is ‘off’ then the roll forward value is going to be similarly ‘off’. Where the portfolio’s exposure to a single asset is relatively large, i.e. co-investments, the integrity of the starting value therefore assumes material importance to the soundness of the roll forward. The following [real] example illustrates this issue, and shows how useful Class 3 data is in its mitigation.

A Real-life Example: Large Exposures and Unanticipated Valuations

The roll forward estimate of UC Investments' alternatives portfolio at fiscal year-end differed from its subsequent GP-reported value, exceeding threshold criteria of materiality[13]. The threshold was met by a single asset, "Co-investment X", which experienced a 42.5% upward valuation during the roll forward period, as shown in Exhibit 9.

The valuation shift was connected to the sale of Co-investment X, which was announced in the month following the roll forward period but included in GP-reporting of the roll forward period. As at the end of the reporting period, however, the valuation shift was unanticipated.

Exhibit 9: Comparison of Roll Forward Estimate and Subsequent GP-Reported Asset Value



As shown below in Exhibit 10, GP-reported value in previous periods showed only modest growth. Stable revenues indicated no fresh M&A activity, which was corroborated by cash flow data. Cash flow, market, and performance data leading up to the roll forward period did not indicate that a significant valuation shift was imminent.

Exhibit 10: Revenue and Valuation Data Prior to Year-End Roll Forward

ALL VALUES IN USD, MM	9/30/2016	12/31/2016	3/31/2017	6/30/2017
LTM Revs	731	746	761	776
Fund A interest	16.95	20.07	20.07	28.64
Fund B interest	8.03	9.51	9.51	13.56
Co-invest interest	108.70	128.90	128.90	183.70
UC Investments Totals	143.67	158.48	158.48	225.91

[13] This case study uses actual quantities, with other data anonymized.

The roll forward procedure did not detect anything 'off' about the starting value, and estimated fair value of the holdings as per Exhibit 11.

Exhibit 11: Roll Forward Values

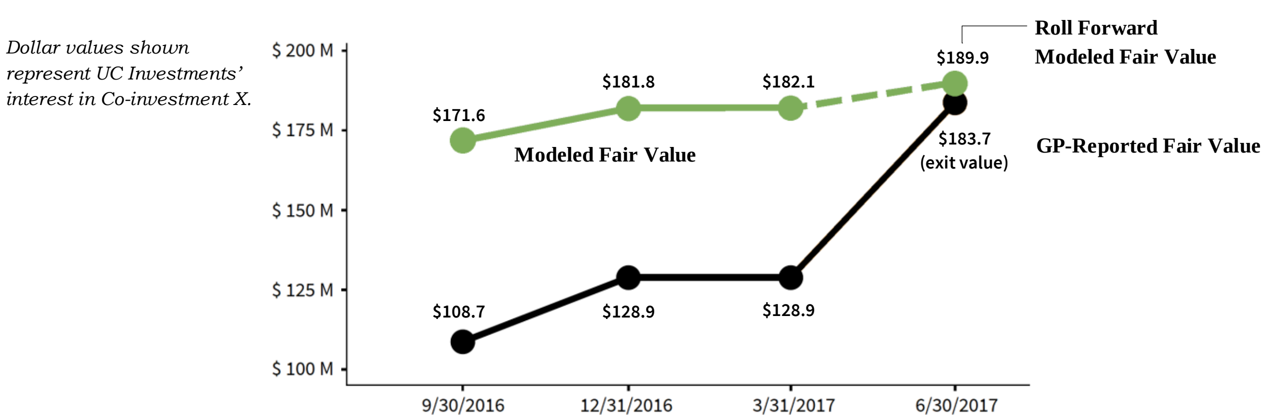
Co-investment X (only)	Starting Value *(LP holdings)*	$ 128,906,401		
	Cash Flow Adjustment		$ 0	
	Market Adjustment		$ 5,614,508	
	Roll Forward Value		$ 134,520,909	
	GP-Reported Value			$ 183,708,484

The delta between the roll forward value and the subsequent GP-reported value is almost $50 million. Upon review, the magnitude of the discrepancy triggered the auditor's materiality thresholds.

A Class 3 Approach

As previously noted, Class 3 data is defined in part by the addition of a company's enterprise value at entry (see Exhibit 1). In the case of Co-investment X, Class 3 data was sourced from fundraising materials provided to UC Investments approximately six months prior to the June 30 year-end.

Exhibit 12: Comparison of Fair Value Estimates (charted)



VALUES IN USD.	9/30/2016	12/31/2016	3/31/2017	6/30/2017
Modeled value	171,785,000	181,945,000	182,096,000	189,870,000
GP-reported value	108,702,159	128,906,401	128,906,401	183,708,484
DIFFERENCE	63,082,841	53,038,599	53,189,599	6,161,516
% DIFFERENCE	58.0%	41.1%	41.3%	3.4%

Using a commercially available approach, described below, the fair value of Co-investment X was mathematically modeled over preceding time periods, with significantly different results than GP-reported fair values. This allowed a starting value (at 3/31/2017) calibrated objectively to market conditions and its fundamental economics from which to carry out the 6/30/2017 roll forward (see Exhibit 12). Compellingly, the roll forward modeled fair value is within less than 4% of the actual exit value, suggesting an objective mechanism to assess the integrity of starting values in the roll forward procedure.

Mathematical Modeling of the Starting Value

Our approach to modeling fair value is conceptually simple, and comprises two key components:

- A standardized measure of the company's economic size; and
- Systematic calibration of the company's size to market, i.e. what is the market paying for a firm size on a given date, in a particular industry.

The key components are produced by commercially available data science technologies that did not require any customization by UC Investments.

The first technology produces a novel quantity, called the fundamental economic value (FEV), which may be thought of as the economic size of a company. The FEV is derived from the company's financial fundamentals and its industry, i.e. contains no forward-looking inputs. It offers a standardized view of both public and private companies (please see Appendix A). Although the predictive accuracy of the FEV to market value (price) is 0.813, as measured by the R-squared statistic, it is completely backward looking. Therefore, a forward-looking component is indicated to connect the FEV contemporaneously to the market.

This second technology creates a custom, non-market-cap-weighted index (modern proxy benchmark), comprised of 50-150 public constituents, constructed on the basis of industry and FEV. The process then tracks the index's FEV over time, using it to decompose the index and determine a market premium, as per *FEV + Premium = Price*. The premium is then mapped back to the FEV of the private asset on a daily basis to solve for the private asset's fair value (for elaboration, see Porter and Porter, 2017).

However, since the modern proxy benchmark has more than 50 constituents, more granular variation in the premium distribution over time can be modeled. To determine exactly where the private company sits on the proxy's premium distribution, and thus quantify its premium in dollar units, Class 3 data is needed. Price at entry allows the asset's premium at entry to be derived. Expressed as a percent of economic size, the premium is then mapped onto the premium distribution of the modern proxy benchmark, and its percentile determined. That percentile is then used to infer the private asset's premium (in dollars) synchronous to the market. This process forms the modeled fair value, a systematically produced and measurably accurate quantity[14].

As seen in Exhibit 12, the asset's modeled fair value at 3/31 was substantially different to the GP-reported fair value. While this could be used to raise a red flag for the roll forward, observe that the valuation deltas for the two preceding time periods are also similarly large. If independent fair value estimation is done quarterly, diverging estimates can be analyzed (with sufficient time to garner GP input) ahead of the year-end portfolio valuation.

Implications for Roll Forward and Operations Innovation

For large exposures, this case study demonstrates that it is both feasible and important to have an objective estimate of the fair value (starting value) that is independent of GP-reported values. This procedural enhancement prioritizes fiduciary oversight and introduces a process that addresses a major limitation of the roll forward procedure. When done frequently, the procedure would allow diverging fair value estimates to be uncovered and either pursued or thoughtfully factored into the roll forward ahead of year-end reporting deadlines.

While a flagging system has practical value, perhaps more far reaching are the implications of enhancing what is being measured and why. Conventional roll forward procedures aim to predict the reported NAV, which we demonstrated may be automated. However, if we consider roll forward accuracy in terms of the decisions it could support, we might become comfortable with an expanded set of roll forward outputs. For instance, is the actuarial process made more effective when the roll forward is accurate to GP-reported valuations that contain bias? The needs of an audit process may be at odds with the needs of an actuarial process, and differ again from the needs of a risk process (although the computational processes overlap significantly).

In short, it may be beneficial for a single process to output multiple quantities that each have high value for a specific process or stakeholder. This would potentially eliminate the need for coarse adjustments or thresholds to roll forward quantities. This study suggests that accuracy can be expressed as multiple, clearly defined quantities in the roll forward procedure without conflict:

- Accuracy to GP (as tested against reported values) – aligned with audit needs.
- Accuracy to long-range values[15] – aligned with actuarial needs.
- Accuracy to market values (as tested against exit values) – aligned with risk needs.

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[14] The authors welcome discussion on rooting the fair value estimate in an empirically tested economic model.
[15] As back tested against multiple market cycles, i.e. 20+ years of data.

The initial focus might be to lift more operations processes out of spreadsheets. However, data, technology and a continuous improvement process allow the roll forward procedure to adapt naturally, particularly in terms of scope, and efficiently cater to emerging needs of operations staff and other stakeholders.

Conclusion

The traditional paradigms of valuation theory and financial reporting suggest that where price is unobservable, subjectivity is acceptable and even necessary to determine fair value. However, these paradigms are impractical for the scale and fiduciary needs of the LP portfolio, both in theory and practice. As a pragmatic work-around to bottom-up appraisals, roll forwards are typically regarded as a static and terminal process, an accounting function not particularly useful beyond reporting. However, the data required to do even a basic roll forward is extensive. With data science technology, the analysis of data and ongoing streams of data represents a compelling opportunity for the LP.

The critical 'zero-to-one' step, demonstrated in this whitepaper to be practical for many LPs, is the operationalization of the data. As shown, data conviction and advanced data science tools have allowed UC Investments to start small, be effective, and pursue innovation opportunities organically. We count automation of the roll forward as 'small' because it previously has been considered an orphaned, stop-gap process. For UC Investments, these qualities significantly reduced project risk, because a feasibility study could be conducted without perturbing day-to-day operations. The results demonstrate that an automated roll forward is feasible within the 'normal' data constraints of today, and that where Class 3 data is available, an intelligent flagging system is possible. As explained in our case study, this has the potential to add value to the management of concentrated exposures, such as in the UC Investments' co-investment portfolio.

The study also exposed opportunities for innovation that arise naturally from the production of reliable portfolio values on a frequent and as needed basis. Quarterly, monthly, even daily runs allow us to re-consider the marginalized function of the roll forward. A continuous and systematically updated depiction of the portfolio provides the means to better estimate the future and explain the past, and theoretically at least, operate more efficiently. Developed as an analytics platform, the roll forward procedure could be exploited to produce outputs suitable for a management focus (investment, risk, operations) in addition to an expanded reporting focus.

Ultimately, the purpose of this paper is to motivate an accelerated data conviction and innovative application of technology among all LPs, not just the giants. By highlighting opportunities now available to data-ready LPs, we hope to spur on modernization efforts – and budgets. This case study is intended to convey information that all practitioners can identify with, and use to get started on what we believe to be an important expedition.

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Appendix A

Accuracy of the Fundamental Economic Value (FEV) to Observable Price.

A dataset of more than 91,000 actual company financials with corresponding transaction price was split into a training subset containing 80% of the data points, and a test subset containing 20% of the data points. A random number generator was used to make the split to control for sensitivity to data selection. A fitted model using only the training subset was created and then used to make predictions for the test subset. The performance of the out-of-sample predictions were found to be on par with – surprisingly just a little bit better than – the in-sample predictions. The observed predictive accuracy of the FEV as measured by the R^2 statistic for the out-of-sample is 0.847, and 0.812 using the entire data set (see Table 1 below). Testing demonstrates that model results were not achieved by overfitting. This is an impressive result that compares favorably with other existing valuation methods.

The FEV technology contains an "Agio" parameter, which specifically controls for multiplier behavior differences between public and private companies. The Agio parameter includes control and liquidity premium adjustments. This results in the FEV's applicability to both publicly and privately held companies on a standardized basis, as demonstrated by the results shown below.

Table 1: FEV Test Results (Pearson R^2)

Pearson R^2	Out of Sample Test Data	Entire Data Set
Public & Private Companies	0.8438075	0.8233954
Private Companies	0.8473803	0.8125333
Public Companies	0.8423252	0.8216545

These test results were produced by an independent academic statistician in 2014. The test methodology has been periodically repeated by FEV Analytics with comparable results, demonstrating that the underlying model has not degraded over time.