An Exploratory Foray into Quantitative Event-Driven modelling: Investigating Earnings Surprise Phenomena and a Journey of Discovery

Saxon Lee

17th of July 2022

Abstract

This paper documents an early exploratory project into the design and methodology of a quantitative event-driven trading model. The primary focus was to investigate the potential for capturing market inefficiencies, specifically post-earnings announcement drift, within public equities, with a view to understanding the practical application of quantitative techniques. The model development involved systematic data collection, the formulation of signals based on earnings surprises, and the construction of a backtesting framework that incorporates foundational concepts of factor analysis and risk metrics. This project represented an initial endeavor to throw my coding chops into the deep end in an attempt to bridge theoretical knowledge with practical implementation in finance. The foundational build of this model was initiated as an independent learning project prior to an internship at Davidson Kempner Capital Management. An enhanced version, developed and utilized for a paper trading exercise during the aforementioned internship, will be kept strictly private indefinitely due to the proprietary nature of work conducted during that period. This paper describes the core architecture and quantitative principles explored, alongside personal reflections on the significant learning process and potential avenues for future development. The accompanying code will be a form of skeleton outline of my work.

Contents

1 Introduction: An Initial Exploration

1.1 Fascination with Market Anomalies: The Case of PEAD

The world of finance is filled with theory, from the Efficient Market Hypothesis (EMH) suggesting prices reflect all information, to observations of persistent market anomalies that challenge this view. As a junior analyst keen to understand market dynamics, the Post-Earnings Announcement Drift (PEAD) presented a particularly intriguing case study. PEAD, the observed tendency for stocks with significant earnings surprises to continue experiencing abnormal returns post-announcement [1], offered a tangible phenomenon to explore the practical application of quantitative methods. This project was born out of a desire to understand if and how such an anomaly could be systematically investigated.

1.2 Project Aims: A Learning-Oriented Approach

This endeavor was primarily an exploratory learning exercise, aimed at dipping my feet into the waters of professional investment work. The objectives were:

- To learn how to translate a theoretical market anomaly (PEAD) into a quantifiable and testable hypothesis.
- To gain hands-on experience in sourcing, processing, and managing financial data, particularly using tools like the Bloomberg API for equities.
- To develop a foundational understanding of signal generation by quantifying "earnings surprise" through various metrics.
- To construct a basic backtesting framework to simulate trading strategies and understand the challenges involved in historical performance evaluation, including the importance of realistic assumptions.
- To explore introductory concepts of risk attribution by attempting to distinguish strategy-specific returns from broad market factor exposures.
- To lay a conceptual groundwork for how such a model might be extended, for instance, to include equity options strategies.

The project was an opportunity to apply newly acquired concepts to real-world financial problems, fostering a deeper appreciation for the complexities and nuances of quantitative trading.

2 Model Functionality and Workflow: A Structured Approach to Exploration

Even in an exploratory project, a structured workflow was deemed essential for clarity and iterative development. Each stage was approached as a learning module.

The conceptual workflow of the exploratory event-driven trading model follows a systematic approach with the following key stages:

1. **Data Collection & Management:** Learning to automate the ingestion and local caching of historical data for earnings, fundamentals, market prices, volume, and factor returns, with an initial exploration of Bloomberg API capabilities.

2. **Signal Generation:** Experimenting with different ways to calculate earnings surprise metrics (EPS surprise, Sales surprise, SUE) and considering how technical indicators might confirm these signals.

3. **Strategy Definition:** Formulating basic systematic trading rules, including simple entry triggers, position sizing ideas (e.g., fixed dollar), and exit conditions (e.g., fixed holding periods).

4. **Backtesting & Simulation:** Building a simplified event-driven backtester to execute the strategy against historical data, with initial attempts to model transaction costs.

5. **Performance Analysis & Attribution:** Evaluating backtested performance using standard metrics and making a first attempt at factor regression to understand return drivers.

6. **Risk Management Assessment:** Introducing basic risk metrics like VaR and CVaR to the simulated portfolio.

This workflow represents the data flow from initial collection through final risk assessment, emphasizing the iterative nature of quantitative model development.

3 Model Mechanics: An Evolving Understanding

3.1 Data Ingestion: The Foundation and Its Challenges

The quality of any quantitative model hinges on the data it consumes. This project provided a practical lesson in the importance of reliable data sources and careful handling.

Earnings Announcement Data:

- *Data Fields Explored:* Historical earnings announcement dates (`ERN_ANN_DT_ACT`), times (`TIME_ANNOUNCEMENT`), reported EPS (`IS_EPS`), sales (`SALES_REV_TURN`), and analyst consensus estimates (`BEST_EPS_CONSENSUS`, `BEST_SALES_CONSENSUS`) via Bloomberg.

- *Learning Insight:* The critical importance of Point-in-Time (PIT) data became immediately apparent. Using consensus data available only *after* an announcement would invalidate any backtest. Fetching T-1 consensus was a key learning point in avoiding lookahead bias. The reliability and cleanliness of this data are paramount.

Market Data:

- *Data Fields Explored:* Daily equity prices (Open, High, Low, Close, Volume). Conceptual exploration of option chain data (`OPT_CHAIN`) and implied volatilities (`OPT_IMPLIED_VOLATILITY_MID`).

- *Learning Insight:* Understanding how corporate actions (splits, dividends) affect historical price series and ensuring data is adjusted correctly is crucial. The sheer volume of market data also highlighted the need for efficient storage and retrieval (caching).

Factor Data:

- *Data Fields Explored:* Daily returns for common risk factors (Mkt-RF, SMB, HML, MOM using ETF proxies like `SPY`, `IWM`, `IVE`, `MTUM`).

- *Learning Insight:* Factors provide a baseline for performance. A strategy might appear profitable but could simply be capturing known risk premia. Accessing and aligning factor data with strategy returns was a practical data management exercise.

Universe Data:

- *Data Fields Explored:* Historical S&P 500 constituents (`INDX_MEMBERS`).
- *Learning Insight:* The concept of survivorship bias was a significant realization. Testing only on current constituents would lead to overly optimistic results. Attempting to reconstruct historical universes, even approximately, added a layer of realism.

3.2 Signal Calculation: Quantifying the "Surprise"

The core of the model lies in defining what constitutes a meaningful earnings surprise.

Core Earnings Surprise Metrics Investigated:

EPS Surprise Percentage:

$$\text{EPS Surprise \%} = \frac{\text{Actual EPS} - \text{PIT Consensus EPS}}{|\text{PIT Consensus EPS}|} \times 100 \tag{1}$$

Standardized Unexpected Earnings (SUE):

$$\text{SUE} = \frac{\text{Actual EPS} - \text{PIT Consensus EPS}}{\text{StdDev(Company's Past N Surprises)}} \tag{2}$$

Learning Insight: SUE appeared more robust as it normalizes the surprise by the company's own historical volatility of surprises, making comparisons across different stocks more meaningful. This was an application of statistical concepts from Kelliher (Chapter 3).

Exploratory Technical Confirmatory Signals: Consideration was given to abnormal volume or significant price gaps around announcements as potential filters, though not deeply implemented in this initial build.

3.3 Strategy Logic: Defining the Rules of Engagement

This involved translating the "surprise" signals into basic trading rules.

- **Entry Criteria (Equities):** Long positions were explored for positive surprises (e.g., SUE > 1.0) on T+1 open, and short positions for negative surprises.
- **Position Sizing (Kelliher Ch. 17):** Initial exploration used fixed dollar allocation. The concept of inverse volatility weighting was considered as a more risk-aware approach.
- **Exit Criteria (Equities):** Primarily fixed holding periods (e.g., 20 days) to observe drift, with a simple percentage stop-loss.

3.4 Backtesting Framework: Simulating the Past

A simplified event-driven backtester was built in Python.

- **Process:** Iterated daily, checking for earnings events, applying entry/exit logic, and tracking a hypothetical portfolio.
- **Transaction Costs (Kelliher Ch. 20.2.2):** A simple percentage-based commission was initially implemented. Recognizing the importance of more realistic costs (bid-ask spreads, market impact) was a key learning for future iterations.

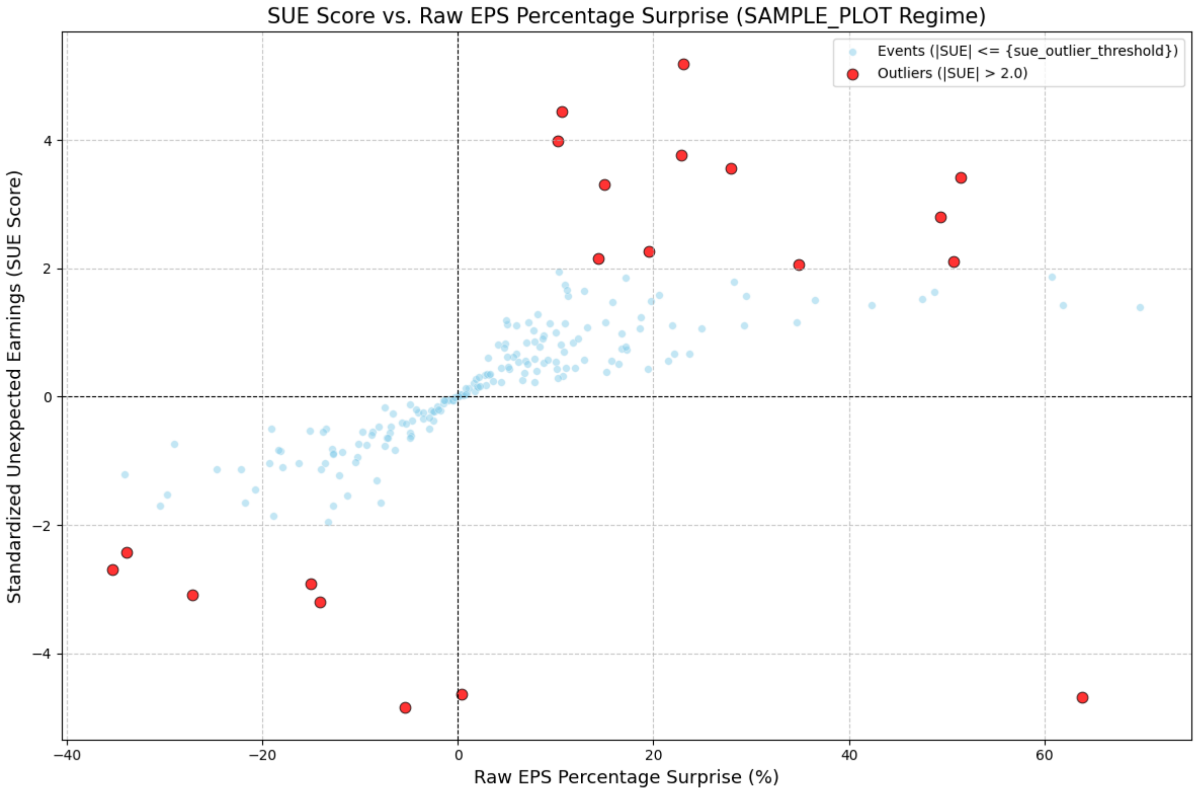

Figure 1: Visual comparison of SUE scores and Raw EPS Percentage Surprise, illustrating how SUE can differentiate earnings surprises, with outliers marked.

4 Striving for Rigor: Foundational Quantitative Practices

Even as an exploratory project, incorporating elements of quantitative rigor was a central goal, guided by principles from texts like Kelliher (2022).

- **Point-in-Time (PIT) Data (Kelliher Ch. 6):** A conscious effort was made to use consensus estimates available *before* announcements.
- **Addressing Survivorship Bias (Kelliher Ch. 6.5.2):** Explored methods to use historical index constituents.
- **Factor Model Integration (Kelliher Ch. 3.3, 18.1):** Attempted a basic factor regression to understand if returns were driven by market movements or potentially unique alpha:
$$R_{\text{strat},t} - R_{f,t} = \alpha + \sum \beta_i \cdot F_{i,t} + \epsilon_t \tag{3}$$
Learning Insight: This was a powerful concept, revealing that apparent profitability might just be beta exposure.
- **Transaction Cost Awareness (Kelliher Ch. 20.2.2):** Realized that even small costs, compounded, can significantly impact strategy viability.
- **Performance Metrics (Kelliher Ch. 20.2.5):** Calculated Sharpe ratio, max drawdown, etc., to get a standardized view of performance.
- **Statistical Robustness (Initial Steps):**

- *Bootstrapping (Kelliher Ch. 3.7, 19.3.2):* Conceptually understood its utility for generating confidence intervals around performance metrics, though not fully implemented in this initial build.
- *Parameter Sensitivity (Kelliher Ch. 7):* Manually tested a few different surprise thresholds and holding periods, recognizing the danger of overfitting (Kelliher Ch. 20.2.4).

- **Risk Awareness (Kelliher Ch. 19):** Calculated historical VaR on the simulated portfolio to get a sense of tail risk.

5 Technical Implementation Notes

- **Language & Libraries:** Python, with `pandas` for data, `numpy` for numerics, `xbbg` for Bloomberg API, `statsmodels` for OLS, and `matplotlib` for plotting.
- **Modularity:** An early attempt at object-oriented design with classes for data collection, signal generation, portfolio, backtesting, and analysis was made to keep the code organized.

6 Personal Reflections, Learning Process, and Insights

This project was my first substantive attempt at building a quantitative trading model from the ground up, and the learning curve was both challenging and very rewarding. It was an exciting opportunity to apply theoretical concepts from finance and statistics, many of which were new to me, to tangible market data and problems especially ahead of my hedge fund internship.

6.1 The Joy of Discovery and Implementation

The most enjoyable aspect was the process of discovery itself – taking an observed market phenomenon like PEAD and trying to systematically test its validity. Bridging the gap between academic theory and practical Python implementation was a significant learning experience, especially when interacting with a professional tool such as the Bloomberg API.

There was a real sense of accomplishment in seeing the different modules (data fetching, signal calculation, backtesting) come together into a cohesive system. The iterative cycle of hypothesizing, coding, testing, and refining, even on a simulated basis, provided a taste of the dynamic nature of quantitative research. I found the challenge of trying to ensure data integrity—grappling with point-in-time data, potential survivorship bias, and the sheer volume of market information—to be a profound lesson in the foundational importance of clean, reliable data.

6.2 Key Insights Gained

- **The Devil is in the Data Details:** Beyond just fetching data, understanding its nuances is critical. The concept of PIT data for consensus estimates was a crucial realization; without it, any backtest is flawed. Similarly, the subtle effects of corporate actions and survivorship bias can dramatically alter perceived historical performance. Data cleanliness and reliability are not just prerequisites but active components of model building.
- **Defining "Surprise" is Non-Trivial:** What constitutes a market-moving "surprise" is more complex than a simple percentage deviation. Exploring metrics like SUE highlighted that normalizing by a stock's own surprise history provides a more robust signal. This insight underscored the need for context in signal generation.

- **Backtesting – A Humbling Experience:** Implementing even a basic backtester revealed the multitude of assumptions involved (transaction costs, slippage, order execution). It became clear that overly optimistic assumptions can easily generate misleadingly positive results. The rigor truly lies in conservative estimation and extensive sensitivity analysis.

- **The Power of Factor Attribution:** The introduction of factor models to decompose strategy returns was a pivotal learning point. A strategy might show profits, but understanding whether this is genuine alpha or merely compensation for bearing systematic risk (like market beta) is essential for true evaluation. This was a practical application of concepts from Kelliher (Ch. 3, 18) and a step towards more professional analysis.

- **Iterative Refinement is Key:** The initial model and signals were rarely optimal. The process involved numerous iterations – tweaking signal definitions, adjusting entry/exit rules, and re-evaluating parameters based on observed (in-sample) results and theoretical soundness.

- **Standing on the Shoulders of Giants:** Throughout this project, I was acutely aware that I was applying concepts and techniques developed by seasoned professionals and academics. A number of resources such as C.Kelliher's book provided a roadmap and a benchmark for rigorous thinking. Aside from this, the learning i have gleaned from those at DKCM has played a significant part too .This experience has only deepened my respect for the depth of knowledge in the both fundamental and quantitative finance and for the investment professionals I had the opportunity to learn from observationally during my internship.

This exploratory project has significantly fueled my enthusiasm to delve deeper into quantitative trading, market microstructure, the intricacies of data integrity, and advanced modelling techniques.

7 Future Enhancements and Adaptations: Broadening the Exploration

This initial model serves as a foundational stepping stone. Numerous avenues for future exploration and enhancement could make it more robust and potentially applicable:

- **Sophisticated Signal Generation:**
  - Explore NLP on earnings call transcripts or financial news to add a qualitative dimension to the "surprise."
  - Investigate analyst revision patterns leading up to announcements.
  - Apply machine learning (Kelliher Ch. 21) to combine multiple weak signals into a more potent composite indicator.

- **Equity Options Layer:**
  - Implement strategies like buying calls/puts based on surprise direction, or volatility strategies like straddles considering the post-earnings IV crush (Kelliher Ch. 8-11, 20.4). This would require robust options data handling and pricing. On a personal note, strategy revision with reading would be required; S.Natenberg, E.Sinclair, N.Taleb amongst other strong shoulders to stand on.

- **Dynamic Portfolio Construction (Kelliher Ch. 17):**
  - If generating multiple concurrent signals, explore techniques beyond equal weighting, such as mean-variance optimization (with robust inputs) or risk parity.
  - Introduce position sizing that adapts to signal strength or market volatility.
- **Advanced Risk Management (Kelliher Ch. 19):**
  - Implement dynamic VaR/CVaR constraints within the backtester.
  - Conduct more rigorous stress tests based on historical crises or simulated factor shocks.
- **Regime-Aware modelling:** Develop a module to identify different market regimes (e.g., high/low volatility, bull/bear markets) and allow strategy parameters or signal interpretations to adapt accordingly.

8 Model Suitability: Reflections on Different Desk Mandates

This project, focused on systematic trading of public equities based on short-to-medium term anomalies, naturally aligns with certain types of quantitative trading desks.

My internship at Davidson Kempner Capital Management was on a distressed investments desk with a primary focus on real estate. This role provided invaluable insights into deep fundamental analysis, valuation of illiquid and complex assets, and the intricacies of private market transactions. The PEAD model, targeting liquid public equities and short-term price movements, has limited direct utility for a desk with such a mandate. The investment horizons, asset characteristics, and analytical toolkits are fundamentally different.

However, the process of building this model and the quantitative skills honed are broadly transferable. This exploratory project helped me understand where such a model *might* find a home:

- **Statistical Arbitrage (StatArb) Desks:** These desks actively seek to profit from short-to-medium term market inefficiencies and mispricings. The PEAD anomaly, if systematically exploitable, fits this paradigm. The model's focus on systematic signal generation, rigorous backtesting, and minimizing transaction costs would be relevant.
- **Quantitative Equity Market Neutral / Long-Short Desks:** The model could form the core of a market-neutral strategy by taking offsetting long positions on positive surprises and short positions on negative surprises. The emphasis on factor attribution to isolate alpha is critical for such mandates.
- **Systematic Event-Driven Hedge Funds:** While many event-driven funds are discretionary, a growing segment uses quantitative approaches to capitalize on a broader range of corporate events, including earnings.
- **Equity Derivatives Desks (with options extension):** Should the model be extended to incorporate equity options strategies around earnings events (e.g., trading volatility or direction via options), it would become relevant for desks specializing in systematic options trading or volatility arbitrage. Understanding IV dynamics around such events would be paramount.

This project, therefore, was not only an exercise in model building but also an exploration into the diverse landscape of quantitative finance and the varied applications of systematic approaches across different trading philosophies and desk mandates. It solidified my interest in market microstructure, the challenges of data reliability in fast-paced environments, and the continuous learning required in quantitative trading.

9 Conclusion: A First Step on a Quantitative Journey

This exploratory Quantitative Event-Driven Trading Model represents an initial, yet significant, step in understanding the practical application of quantitative principles to financial markets. The project's journey from investigating the PEAD anomaly to developing a (simulated) systematic trading framework has been an invaluable learning experience. It has highlighted the critical importance of data integrity, the nuances of signal construction, the necessity of rigorous backtesting with conservative assumptions, and the insightful power of factor attribution.

The development of this model has underscored that quantitative finance is a dynamic interplay of financial theory, statistical analysis, data science, and software engineering. While this initial build was a personal learning endeavor, it has laid a foundation of skills and kindled a strong enthusiasm for further exploration into more advanced quantitative techniques, market microstructure, and the sophisticated use of data in trading.

It is important to reiterate the development context of this project. The foundational build of this model, focusing on the core concepts of earnings surprise analysis and the initial backtesting framework, was initiated as an independent research and learning project prior to my internship at Davidson Kempner Capital Management. During the internship, an enhanced version of this model was developed and utilized for a paper trading exercise; the specifics of this enhanced version, including any proprietary modifications or performance data, will be kept strictly private indefinitely due to the confidential nature of work and intellectual property developed during that period. I am very appreciative of my experience at Davidson Kempner and for the time of the professionals that have given me a lot of ideas for how to improve moving forward. This paper serves to document the underlying quantitative principles, architectural design, and the significant learning journey undertaken in creating this exploratory model for academic and research purposes.

References

[1] Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting research*, 1–36.

[2] Kelliher, C. (2022). *Quantitative Finance With Python: A Practical Guide to Investment Management, Trading, and Financial Engineering.* Chapman & Hall/CRC.