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PREDICTING UNEXPECTED EARNINGS RISK

Introducing the Erie – A Stock Screening and Risk Management Tool

- **The Grandmasters of Predicting Earnings Risk.** As the market's chessboard unfolds, company earnings announcement represents one of the largest sources of firm-specific risk and opportunities. In this research, we continue to explore the board game of bridging the gap between the options and stock markets (see *Know Your Options* for Part I of this research series). In particular, we develop a suite of tools to measure earnings uncertainty during the reporting season.
- **Capturing Earnings Uncertainty.** Using kernel regression, we reconstruct the options IV (Implied Volatility) surface. Then, depending on the horizon of the next pending earnings release, we develop a company-level earnings risk measure – the EIV (Earnings-Induced Volatility) and an associated signal – earnings uncertainty. Our empirical analysis suggests that the earnings uncertainty measure is highly accurate in quantifying the price fluctuations around earnings news.
- **Identifying Shorting Opportunities.** Next, using an event study framework, we test the efficacy of our earnings uncertainty and other metrics (e.g., earnings dispersion and realized volatility) in screening for short candidates. The Erie (Earnings Risk Insight and Estimate) model leverages short-term growth expectations, earnings uncertainty, and our systematic earnings prediction model Emi (see *Systematic Earnings Prediction*) to identify companies with the largest unexpected earnings risk.
- **Incorporating Earnings Risk in Portfolio Construction and Hedging.** Multifactor equity risk models do not typically take into account the idiosyncratic nature of earnings uncertainty. On the other hand, options traders pay particular attention to earnings news, but normally do not use multifactor equity risk models, leading to an overestimation of idiosyncratic volatility. Our Erie-Risk model – incorporating both traditional risk factors and earnings uncertainty – boosts the accuracy of our baseline Wolfe QES Standard Risk Model considerably, especially during earnings season. More importantly, incorporating earnings risk also leads to active portfolios with higher Sharpe ratio (IR), lower realized volatility and downside risk. The Erie-Risk can also be applied to construct custom hedges against the unintentional/undesirable earnings uncertainty risk.

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A Letter to Our Readers

In this research, we continue our pursuit of bridging the gap between the options and stock markets (see *Know Your Options*, Li, et a. [2023] for Part I of this research series). In particular, we develop a suite of tools to measure earnings uncertainty during the reporting season.

Most financial market participants are well aware of the fact that earnings announcement is one of the primary sources of company-specific risk. Consequently, many investors tend to avoid taking significant positions (either long or short) around earnings announcement dates. At the same time, earnings releases also offer enormous arbitrage opportunities. In fact, the so-called PEAD (Post-Earnings Announcement Drift) is one of the most studied anomalies both in academia and by practitioners (see Foster, et al [1984], Luo, et al [2020]).

First, using kernel regression, we reconstruct the option IV (Implied Volatility) surface. Then, depending on the horizon of the next pending earnings release, we develop a company-level earnings risk measure – the EIV (Earnings-Induced Volatility) and an associated signal – earnings uncertainty. Our empirical analysis suggests that the earnings uncertainty measure is highly accurate in quantifying the price fluctuations around earnings news.

Next, using an event study framework, we test the efficacy of our earnings uncertainty and other metrics (e.g., earnings dispersion and realized volatility) in screening for short candidates. The Erie (Earnings Risk Insight and Estimate) model leverages earnings growth expectations, earnings uncertainty, and our systematic earnings prediction model Emi (see *Systematic Earnings Prediction*, Luo, et al [2020]) to identify companies with the largest unexpected earnings risk.

Lastly, we demonstrate how to incorporate earnings uncertainty in the portfolio construction process. Multifactor equity risk models used to be exclusively adopted by only quantitative portfolio managers. However, in recent years, we have seen a rapid adoption by fundamental and discretionary managers. Commercial risk models do not take into account the idiosyncratic nature of earnings uncertainty. We construct a custom risk model – the Erie-Risk – that incorporates both traditional risk factors and earnings uncertainty. We find that the Erie-Risk boosts the accuracy of our baseline Wolfe QES Standard Risk Model considerably, especially on the idiosyncratic component and particularly during earnings season. The Erie-Risk not only enjoys high statistical accuracy, but also leads to active portfolios with higher Sharpe ratio (IR), lower realized volatility and downside risk. For managers who do not use mean-variance portfolio optimizer, they can easily apply the Erie-Risk to construct custom hedges against the unintentional/undesirable earnings uncertainty risk.

Regards,

Victor, Yin, Javed, and the QES Team

Options-Based Earnings Uncertainty

Our first task focuses on extracting stock-level uncertainty induced by earnings announcements – a concept we call the PMIE (Price Movement Induced by Earnings). Specifically, we want to understand whether options contracts reveal additional information that is not captured by past earnings, company fundamentals, and other publicly available data. Our primary objective is to develop a model-based methodology to estimate earnings uncertainty systematically and accurately using options IV (Implied Volatility) term structure. This can reveal both potentially profitable investment opportunities and add forward-looking insights in equity risk models.

Background

Options typically expire on Fridays, but the exact date varies. Traditionally, standard options have a pre-determined expiration date on the third Friday of each month. Other options, particularly on popular large cap stocks, offer weekly expiration dates. These weekly options usually expire on Fridays, except when Friday is a market holiday. In such cases, the expiration might fall on a Thursday. The actual expiration time is typically at the end of the trading day on the expiration date. There are also longer-term options, like LEAPS (Long-Term Equity Anticipation Securities), which may expire annually or even longer. We do not consider Day-Expiry or daily options in this research, which are not (yet) as common as their longer-term counterparts, like weekly or monthly options. Due to their short lifespan, daily options can be particularly risky and are generally used for more speculative purposes.

Earnings announcement represents one of the most important corporate events, revealing market-moving news and shaping investors' future expectations. Patton and Verardo [2012] study the impact of earnings announcement on beta risk, while Savor and Wilson [2016] explore the impact of macroeconomic news on stock volatility. Stock prices often move wildly around earnings announcements.

Such market expectations on earnings releases should be at least partially reflected in the risk-neutral distribution and the shape of the IV curve. Dubinsky, et al [2019] document a notable increase in IV around earnings announcements. Alexiou, et al [2023] find a general concavity in the IV curve before earnings announcement, a pervasive feature indicating the likelihood of significant stock price changes.

Algorithm Design

In this section, we present our method of assessing options market expectations on the immediate forthcoming earnings (i.e., FQ1) announcement through the lens of IV term structures, i.e., IV over different maturities. As detailed in *Know Your Options* (see Li, et a. [2023]), IV reflects the options market's expectation of how much an asset's price will fluctuate in the future, based on the current prices of the asset's options. In practice, IV varies by the maturity of options, forming the IV term structure.

What are We Predicting?

The target variable that we aim to predict is the price movement of a given company on induced purely by earnings news. Unlike our systematic earnings prediction model – the Emi (see *Systematic Earnings Prediction*, Luo, et al [2020] for details), in this research, we are less concerned about the direction whether a company will beat or miss earnings expectations. Instead, we focus on the risk or uncertainty of the earnings prediction. Specifically, our target variable – the PMIE (Price Movement Induced by Earnings) – is defined as the absolute return on the earnings announcement date:

$$PMIE_i^{t^{EA}} = \left| r_i^{t^{EA}} \right|$$

Where,

$PMIE_i^{t^{EA}}$ is our target variable,

t^{EA} is the earnings announcement date, and

$r_i^{t^{EA}}$ is the return of stock i and earnings announcement date t^{EA}.

Although one particular stock's price fluctuation on its earnings announcement date can also be influenced by factors other than earnings, in aggregate, earnings should be the primary driver of volatility for a large sample of companies.

An Overview

To accurately estimate earnings uncertainty (i.e., the PMIE) using options data, it is crucial to distill the specific contribution of the earnings event from the observed IV curve. The aim of our algorithm is to processes the point-in-time IV surface to isolate the portion of the volatility attributed to the earnings announcement. This involves differentiating between the systematic IV already present in the options market (i.e., the "normative" IV) and the additional volatility expected due to the idiosyncratic event like a corporate earnings announcement. There are three steps in our main calculation:

- First, we assume that the observed IV (denoted IV_{Obs}) associated with the options contracts that are expiring immediately after the forthcoming earnings announcement is due to a combination of earnings uncertainty and normative volatility.
- Next, we estimate the baseline normative IV (called $\widehat{IV}_{Norm}$) that is orthogonal to earnings announcements, using a kernel regression approach (see details below).
- Lastly, the difference between IV_{Obs} and $\widehat{IV}_{Norm}$ is the element of primary interest to us, i.e., options IV associated with the pending earnings release: $IV_{Earnings} = IV_{Obs} - \widehat{IV}_{Norm}$.

The exact algorithm that computes $IV_{Earnings}$ differs depending on the duration from current date (or point date for historical data) to the next earnings release date:

- **Case 1 – Distant Earnings Announcement (DEA).** In the first case, the forthcoming earnings announcement date is relatively far from the current date or point date (e.g., more than one month away). Because of earnings uncertainty is towards the backend, the IV term structure often shows an upward-sloping trend, peaking around the next earnings announcement date.
- **Case 2 – Imminent Earnings Announcement (IEA).** In this case, the earnings release date is imminent (e.g., a few days from current date). In such occasions, near-term options contracts mostly reflect the uncertainty with pending earnings. On the contrary, the long-dated contracts are typically associated with longer-term expectations, whereas the next earnings play a minor role. As a result, we often observe a downward-sloping IV curve. Specifically, IEA is defined as those occasions with only one options maturity or no options before the next earnings announcement date.

In addition to earnings announcement date t^{EA}, we also need to define two important dates:

- **Expiry date immediately before earnings announcement ($\boldsymbol{T_{Before}}$)**: This is defined as the expiry date of the options contract with the closest expiry date immediately prior to the pending earnings announcement date. Note that $T_{Before} \le t^{EA}$.
- **Expiry date immediately after earnings announcement ($\boldsymbol{T_{After}}$)**: This is defined as the expiry date of the options contract maturing immediately after the earnings announcement date. Obviously, $T_{After} > t^{EA}$.

Estimating Normative IV using Kernel Regression

How to estimate the baseline normative IV that is unrelated to earnings uncertainty is not a trivial task. Options data, similar to most financial datasets, contains missing values, outliers, errors and omissions. We employ a kernel regression method to estimate and extrapolate the normative IV.

The kernel regression method is particularly valuable in the financial context as a "smooth" estimation technique with noisy market data. It is a non-parametric approach used for smoothing and interpolating data points. The core concept revolves around using a kernel function to weigh nearby observations more heavily than distant ones, thereby producing a smooth best-fit curve for a given dataset.

Given the observed sample dependent and independent variables y_i and x_i, the mathematical formulation of the one-dimensional kernel regression can be expressed as follows:

$$\hat{y}(x) = \frac{\sum_{i=1}^{N} k_h(x - x_i) y_i}{\sum_{i=1}^{N} k_h(x - x_i)}$$

Where, the kernel function $k_h(.)$ assigns weights to the observed data points, with the subscript h indicating the bandwidth of the kernel. The estimator essentially computes a weighted average of y_i values, where the weights are determined by how close each x_i is to x, as measured by the kernel function. The numerator adds up all the y_i values, each weighted by the kernel function evaluated at the distance from x. The denominator is a normalization factor that ensure the weights sum to 100%.

The bandwidth is a crucial hyperparameter that determines the smoothness of the resulting curve – a smaller h leads to a curve that closely follows the data points (but at the risk of overfitting), while a larger h produces a smoother curve (but may overlook some of the finer details). Similar to most other machine learning and statistical techniques, it is all about the bias-variance trade-off (see Luo, et al [2017], *Style Rotation, Machine Learning, and the Quantum LEAP*, for details).

Given observed IV $\sigma(t_i)$ at maturity t_i, the kernel regression is designed to approximate unobserved options IV $\hat{\sigma}(t)$ based on the observed $\sigma(t_i)$ at different maturities t_i:

$$\hat{\sigma}(t) = \frac{\sum_{i=1}^{N} k_h(t^{EA} - t_i)\sigma(t_i)}{\sum_{i=1}^{N} k_h(t^{EA} - t_i)}$$

As we will further elaborate later, the kernel regression model estimates the normative IV curve, using nearby observed IV maturing at various t_i dates around t^{EA}. These neighboring IV's are weighted by their maturing distance to the earnings announcement date $t^{EA} - t_i$. The bandwidth parameter is set to the average distance between observed maturities.

Missing Value Imputation for (very) Short and Long Maturity Options

For many stocks, we only have liquid options with medium durations of maturity. IV data is often missing for options with very short (e.g., a few days) or long (e.g., more than six months) maturities. However, these data points are important for our kernel regression, in order to capture the tails of the options IV term structure. The tails can significantly influence the estimation of normative IV.

In our research, we employ the linear tail extrapolation technique (see Ulrich and Walther [2020]) to extend the volatility surface into regions where data is sparse, particularly for very short-term and long-term options.

For the left tail of extremely short maturity, IV's of the first three shortest maturities are used for linear elastic net regression:

$$\sigma_i = \alpha + \beta t_i + \varepsilon_i$$

Where $\varepsilon_i \sim i.i.d.$

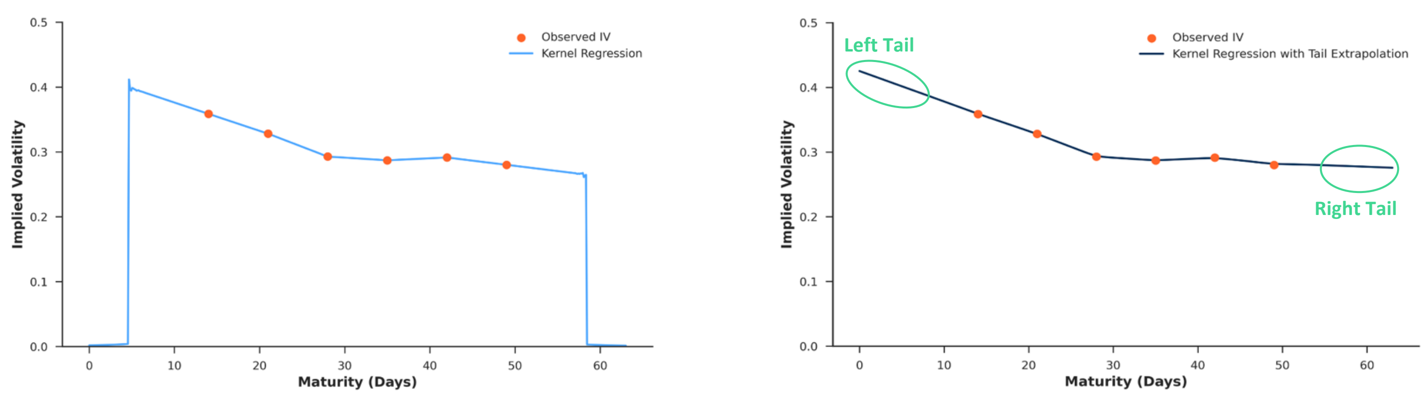
The left-tail extrapolation starts from the three shortest duration options and proceeds backwards in increments until maturity of zero day. The right tail follows a similar approach, using IV's of the longest maturity contracts, and we extrapolate to the longest desired duration.

As shown in Figure 1(A), without missing value imputation, IV falls to zero (or missing) for very short and long maturities. On the other hand, our extrapolation algorithm delivers a more intuitive message and paints a more comprehensive picture of the IV surface. It ensures that the kernel regression in the previous section incorporates both the actual observed volatilities and the extrapolated IV's at the tails, leading to a more accurate and complete depiction of the IV landscape across different maturities.

Figure 1 Effect of Tail Extrapolation on the Kernel Regression Fitting of Apple Inc.'s IV Term Structure

A) Without Tail Extrapolation

B) With Tail Extrapolation



Sources: Wolfe Research Luo's QES

Case 1 – DEA

As mentioned earlier, when the next earnings (i.e., FQ1) announcement date is relatively far from the current date or point date (e.g., more than one month away), the IV term structure often shows an upward trend. This occurs because the short-term IV curve does not reflect the uncertainty of the upcoming earnings announcement.

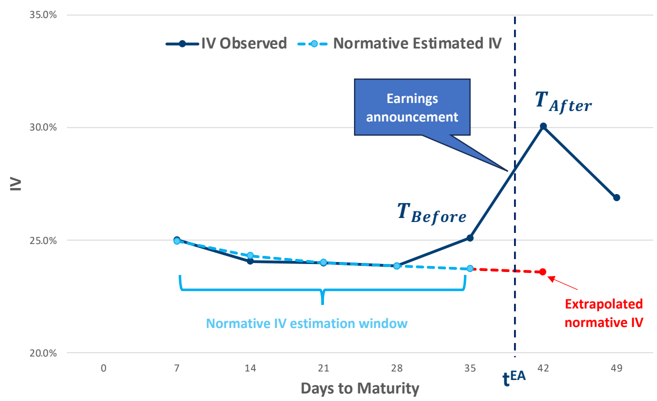
As shown in Figure 2(A), in this case, we apply the kernel regression model to estimate the baseline IV curve using options expiring between the current date and the next earnings announcement date, T_{Before} (i.e., options expiring prior to the forthcoming earnings announcement). The baseline IV curve presumably reflects a "normal" environment where earnings play a secondary role. Then, we apply the fitted model above to extrapolate $\widehat{IV}_{Norm}$ (i.e., the IV without earnings impact) to date T_{After}.

Then, earnings variance is defined as the difference (in variance) between observed options IV at date T_{After} (i.e., IV_{Obs}) and our estimated normative $\widehat{IV}_{Norm}$ on the same date (see Figure 2B):

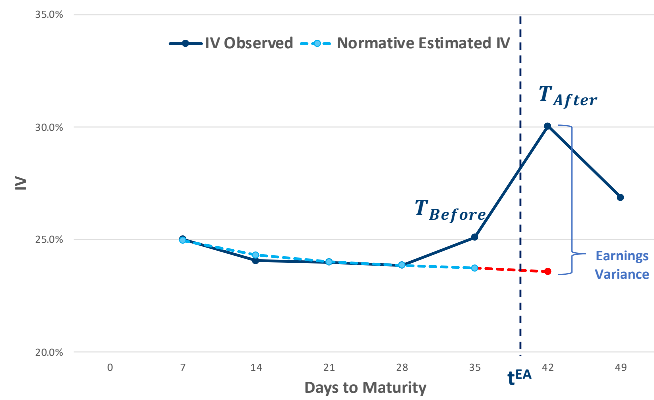
$$EarningsVariance = {IV_{Obs}}^2 - {\widehat{IV}_{Norm}}^2$$

Figure 2 Estimating Earnings Variance, Case 1 – DEA (Distant Earnings Announcement)

A) Normative IV Estimation and Prediction



B) Earnings Uncertainty



Sources: Wolfe Research Luo's QES

Case 2 – IEA

As the earnings release date approaches, near-term options contracts begin to encapsulate earnings uncertainty. On the contrary, the long dated contracts are likely to reflect longer-term expectations, whereas the pending earnings play a minor role. As a result, we often observe a downward-sloping IV curve.

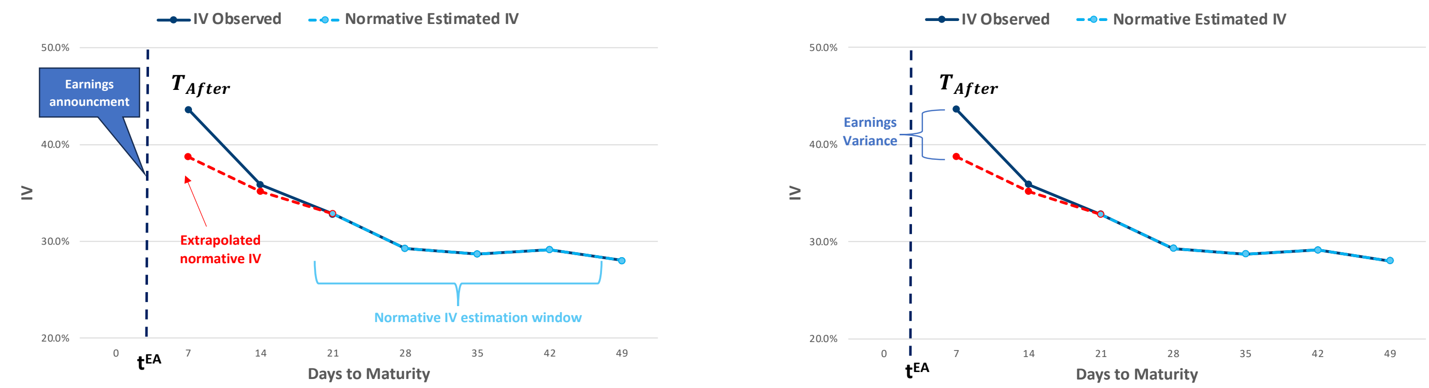
In the IEA case, we conduct the kernel regression model to estimate the normative IV curve using options with expiry dates at least two weeks (but no more than two months) post the forthcoming earnings announcement date t^{EA}, to ensure that we only use those options contracts relatively unrelated to the pending earnings (see Figure 3A). We do not estimate the normative curve when there are less than three observed contract maturity data points. By choosing options that are no more than two months after the next (i.e., FQ1) earnings date, our model avoids the contamination from the second forward earnings (i.e., FQ2) announcement. Next, we backcast the fitted model above to date T_{After}, in order to estimate $\widehat{IV}_{Norm}$ (i.e., the IV without earnings impact) on date T_{After}.

The definition of earnings variance is exactly the same as the DEA case, i.e., the difference (in variance) between observed options IV at date T_{After} (i.e., IV_{Obs}) and our estimated normative $\widehat{IV}_{Norm}$ on the same date (see Figure 3B):

$$EarningsVariance = {IV_{Obs}}^2 - {\widehat{IV}_{Norm}}^2$$

Figure 3 Earnings Variance, Case 2 – IEA (Imminent Earnings Announcement)

A) Normative IV Estimation **B) Earnings Associated IV**



Sources: Wolfe Research Luo's QES

Defining Earnings Uncertainty

Recall that our earnings variance measure is the difference between observed and estimated normative options implied variance:

$$EarningsVariance = {IV_{Obs}}^2 - {\widehat{IV}_{Norm}}^2$$

To come up with a metric that has the same dimension and scale as our target variable, the PMIE, we make a few more adjustments.

First, we add a robustness test. As explained in previous sections, we typically observe an upward-sloping IV curve in the DEA case and a downward-sloping IV shape in the IEA case. However, there are certainly occasions that are different from the expected patterns. As a result, the expected upward/downward IV curve may turn out to be flat or inverted. Because we are primarily interested in finding companies with large earnings uncertainty, we only compute earnings uncertainty for those companies with the expected IV term structure (i.e., upward-sloping IV curve for DEA and downward-sloping for IEA).

Second, we re-scale our (annual) earnings variance measure to a "volatility" term ($\sigma_{Earnings}$) corresponding to the duration around earnings announcement day. We define this variable as EIV (Earnings Induced Volatility).

$$EIV = \sqrt{\frac{(T_{After} - CurrentDate)}{252}\left({IV_{Obs}}^2 - {\widehat{IV}_{Norm}}^2\right)}$$

Next, assuming that the component of stock returns associated with earnings uncertainty are normally distributed with $\sigma_{Earnings}$ being the standard deviation, we can also deduce the implied magnitude of stock price fluctuation or our final measure of earnings uncertainty. Specifically, $EarningsUncertainty$ is defined as the expected mean of the absolute price movement induced by earnings (i.e., the PMIE):

$$EarningsUncertainty = \mathbb{E}\left[\left|PMIE_i^{t^{EA}}\right|\right] = \int_{-\infty}^{\infty} |x| \, f_{\mathcal{N}}(x) \, dx = \sqrt{\frac{2}{\pi}} \times EIV$$

It is important to highlight that the EIV and earnings uncertainty are almost identical – the only difference lies in the scaling factor $\sqrt{2/\pi}$. In this research, we switch between earnings uncertainty and EIV, depending on the specific context. However, stock ranking or empirical analysis should be the same, regardless which metric is used.

Evaluating the Earnings Risk Forecast

Having the predicted earnings uncertainty measure, the next natural question is how to evaluate the accuracy of our forecast. There are three additional steps involved:

- Defining actual or realized PMIE;
- Introducing a naïve benchmark model that can be deployed easily to predict earnings risk; and
- Assessing and comparing the performance accuracy of our earnings uncertainty with the benchmark model

Realized Price Movement on Earnings Announcement Date

Because our earnings uncertainty measure is a proxy for price movements induced by earnings risk, the actual or realized PMIE is simply the absolute value of stock return on the earnings announcement date.

A Benchmark Model

Instead of using options IV curve, we could certainly extrapolate past PMIE, e.g., the rolling three-year (i.e., 12 quarters) average PMIE as our prediction of next earnings risk.

$$\overline{PMIE_i} = \frac{1}{12} \sum_{t=Q-1}^{Q-12} PMIE_i^t$$

Where, $PMIE_i^t$ is the absolute value of daily stock return on each of the earnings announcement dates in the past three years (i.e., 12 quarters).

Performance Metric – the EBS

Next, we introduce our performance measurement metric – the EBS (Earnings Bias Statistic), formulated to assess the accuracy of our earnings uncertainty. Readers who are familiar with equity risk models will note that the EBS methodology follows closely with the bias statistic used to assess risk model accuracy (see Mueller et al [1993] and *Risk Model Deep Dive – Forecasting Correlation*, Elledge, et al [2022] for details). Specifically, the EBS is defined as follows:

$$EBS = \frac{1}{N} \sum_{i=1}^{N} \frac{PMIE_i^{t^{EA}}}{EarningsUncertainty}$$

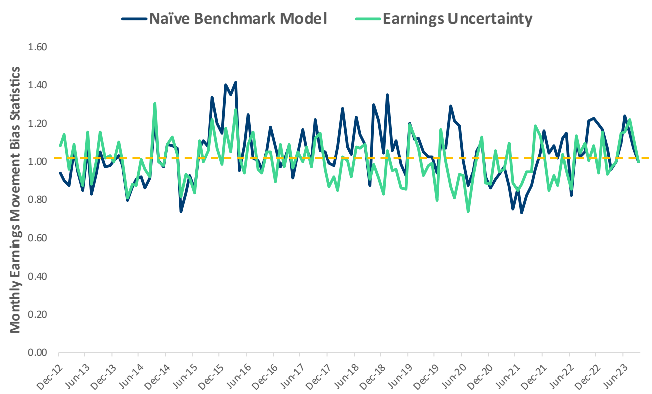
Where, $PMIE_i^{t^{EA}}$ represents the realized price movement of stock i on its earnings announcement day, and the average is computed cross-sectionally for all stocks (N) in our universe.

An unbiased estimate of the earnings induced price movement, should yield an average EBS close to one. On the other hand, underestimation (overestimation) of earnings risk will have a bias statistic greater (lower) than one.

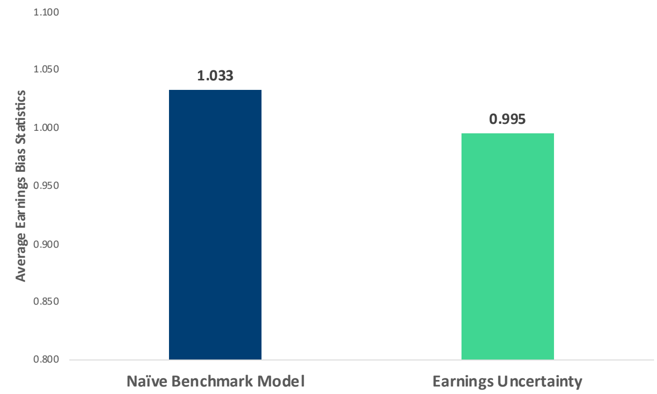
As shown in Figure 4(A), our earnings uncertainty measure tracks actual earning risk much closer than the naïve benchmark (which simply extrapolates past earnings risk) with an EBS closer to one. Over the past decade, the average realized EBS of our earnings uncertainty factor is only slightly below one (at 0.995), with an estimation error about 85% lower than the naïve benchmark (see Figure 4B).

Figure 4 Average Cross-Sectional EBS

A) EBS Time Series



B) Long-Term Average EBS



Sources: NewMark Risk, Bloomberg Finance LLP, MSCI, FTSE Russell, Markit, RavenPack, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

TRADING AND HEDGING EARNINGS UNCERTAINTY

Given the dominant nature of earnings risk to a company's share performance, in this section, we are introducing our Erie (Earnings Risk Insight and Estimate) screening tool. For active managers, the Erie helps them to identify stocks that are exposed to material downside earnings risk and therefore, are likely to underperform around earnings announcement dates. Those stocks are candidates for shorting. For other managers who want to avoid taking excessive earnings risk, the Erie can assist in identifying stocks to avoid or hedge.

SCREENING FOR EARNINGS RISK – FEATURE SET

In order to identify the most powerful factors to quantify earnings risk and construct the Erie model, we start our analysis with the following features (see Figure 5):

- **Near-term growth expectations** (FQ1 consensus estimated earnings growth) and near-term (FQ1) **dispersion in consensus earnings expectations** set the scene. Companies with slow growth expectations and high consensus earnings dispersions often underperform their peers.
- In addition to earnings uncertainty, we also incorporate firms that are mostly like to miss their earnings expectations. Here we leverage the **Emi** (Earnings Metric Insight) model. As detailed in *Systematic Earnings Prediction*, Luo, et al [2020] for details), the EMI model is designed to predict each of the subsequent eight quarters of earnings, i.e., FQ1 to FQ8 EPS, for roughly 2,400, 400, and 1,000 companies in the US, Europe, and Asia including Japan and China A shares. The EMI model is substantially more accurate at predicting firm-level EPS for the forthcoming eight quarters than sell-side consensus. EMI combines both traditional econometrics and machine learning techniques.
- **Options sentiment (IV Spread).** Following Lei, et al [2020] and *Know Your Options* (see Li, et a. [2023]), we proxy options sentiment using the IV spread between ATM (At-The-Money) call and put options (with the same strike price and expiry date). A high IV spread indicates calls are more expensive than puts, suggestions that options investors on average are more bullish on the underlying stock. The opposite holds when puts are more expensive than calls. This metric captures the influence of informed trading, especially evident in the periods leading up to significant corporate events such as earnings announcements.
- **Realized volatility** (computed using rolling one-month daily returns) is a standard metric to assess near-term volatility of a stock. The low risk anomaly suggests that stocks with higher volatility typically deliver suboptimal returns than their low volatility peers (see *Thinking (Risk Models), Fast and Slow*, Wang, et al [2020]).
- **Earnings uncertainty** has been the primary focus of this research. As discussed in the previous section, we develop the earnings uncertainty metric using the options IV curve. We expect firms with large earnings uncertainty (and EIV) to underperform the market around earnings announcement days.
- **EVRP (Earnings induced Volatility Risk Premium).** The EVRP factor is defined as the difference between our estimated earnings induced volatility (i.e., EIV) using options IV curve and one-week realized volatility. The EVRP is designed to explore potential mispricing between the options and equity markets. In *Know Your Options* (see Li, et a. [2023]), we study a similar concept called VRP (Volatility Risk Premium) at the stock level and find it to be predictive of

future stock return and volatility. Similarly, we design the VRP (Variance Risk Premium) at the aggregate level and find it to be highly predictive of overall market sentiment (see *Risk-On and Risk-Off Again?*, Luo, et al [2017]). The relationship between EVRP and future stock returns is not obvious. Consequently, we will rely on empirical testing to decide which direction to take.

Following *Signal Research and Multifactor Models* (see Luo, et al [2017]), we sort all stocks in our investment universe by each of the above factors and models from low to high into five quintile portfolios, where Q1 represents the bottom quintile (i.e., bottom 20% of stocks with the lowest scores) and Q5 includes stocks with the highest scores. Please note that factors/models are in their original/natural direction. For example, FQ1 earnings dispersion would rank stocks with the lowest dispersion to the highest, and similarly, the Emi model would sort stocks with the highest probability to beat earnings expectations to the lowest (or the highest probability to miss earnings).

We further normalize each stock for each signal at each point-in-time using a rolling three-month lookback window. This ensures each factor/model to be comparable across different companies and over time.

Our Erie screening is based on the US large cap universe, roughly the Russell 1000 index constituents. It is available on a daily basis. Readers who are interested in the Erie model should contact your Wolfe Research sales representative or us directly for details.

Figure 5 Feature Set – Quantifying Earnings Risk

Factor Definition	Description	Expected Direction
Growth Expectation	FQ1 analyst consensus median EPS growth	Ascending
Earnings Dispersion	Standard deviation of FQ1 analyst estimates scaled by price	Descending
Predicted Earnings Surprise	Predicted FQ1 earnings surprise (i.e., whether a company will beat or miss consensus earnings expectations) using the QES Emi model	Ascending
Options Sentiment	IV spread between ATM call and put options	Ascending
Realized Volatility	Rolling 1-month realized volatility	Descending
Earnings Uncertainty	As detailed in the previous section, earnings uncertainty is our prediction of PMIE using options IV curve	Descending
EVRP (Earnings Volatility Risk Premium)	The difference between our estimated earnings induced volatility (i.e., EIV) using options IV curve and one-week realized volatility	Unknown

Sources: Wolfe Research Luo's QES

EVENT BACKTESTING

We use an event study framework to assess the efficacy of our sentiment signal. Consistent with *Systematic Earnings Prediction*, Luo, et al [2020], to avoid look-ahead bias, we lag all of our signals by one day, i.e., one business day post the earnings announcement date, when we conduct our event study.

Our event study methodology follows *Beyond Fake News – Extracting Signals from Noisy News, Social Media, and Events* (see Rohal, et al [2019]). Essentially, we track the average performance of companies around earnings announcement date, broken down by each of our factors/models in Figure 5. It is critical to control for market return in event studies. In our evaluation framework, excess return is defined as stock return relative to the Russell 1000 total index return. We plot performance one month prior to and two months post the earnings announcement date. The backtesting is conducted from 2012 onwards.

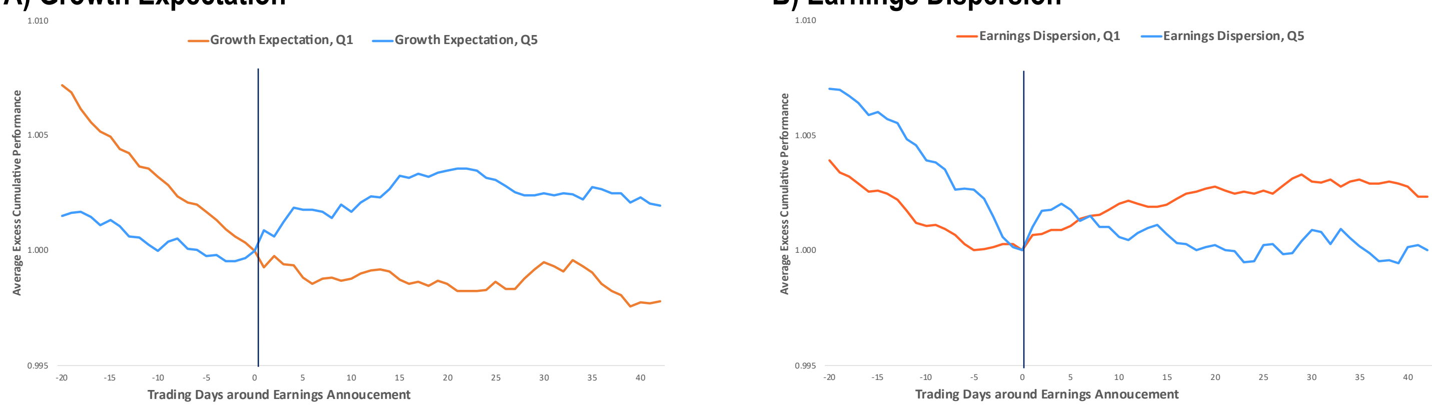
Growth Expectations and Earnings Dispersion

As shown in Figure 6(A), the market fails to fully account for companies with strong growth expectations (in Q5) – the average performance was flat prior to earnings announcement, followed by decent outperformance in the month post earnings releases. On the other hand, the underperformance of firms with slow growth expectations (in Q1) is pronounced both before and after earnings news.

In terms of earnings dispersion, on average, investors again appear to underreact to information. Stocks with low earnings dispersion (Q1) fall slightly leading up to earnings, but then recover. On the contrary, firms with large dispersions (in Q5) recoup some of the pre-announcement loss once earnings uncertainty is resolved, but then stay flat.

Figure 6 Performance around Earnings Announcement, Growth Expectation and Earnings Dispersion

A) Growth Expectation **B) Earnings Dispersion**

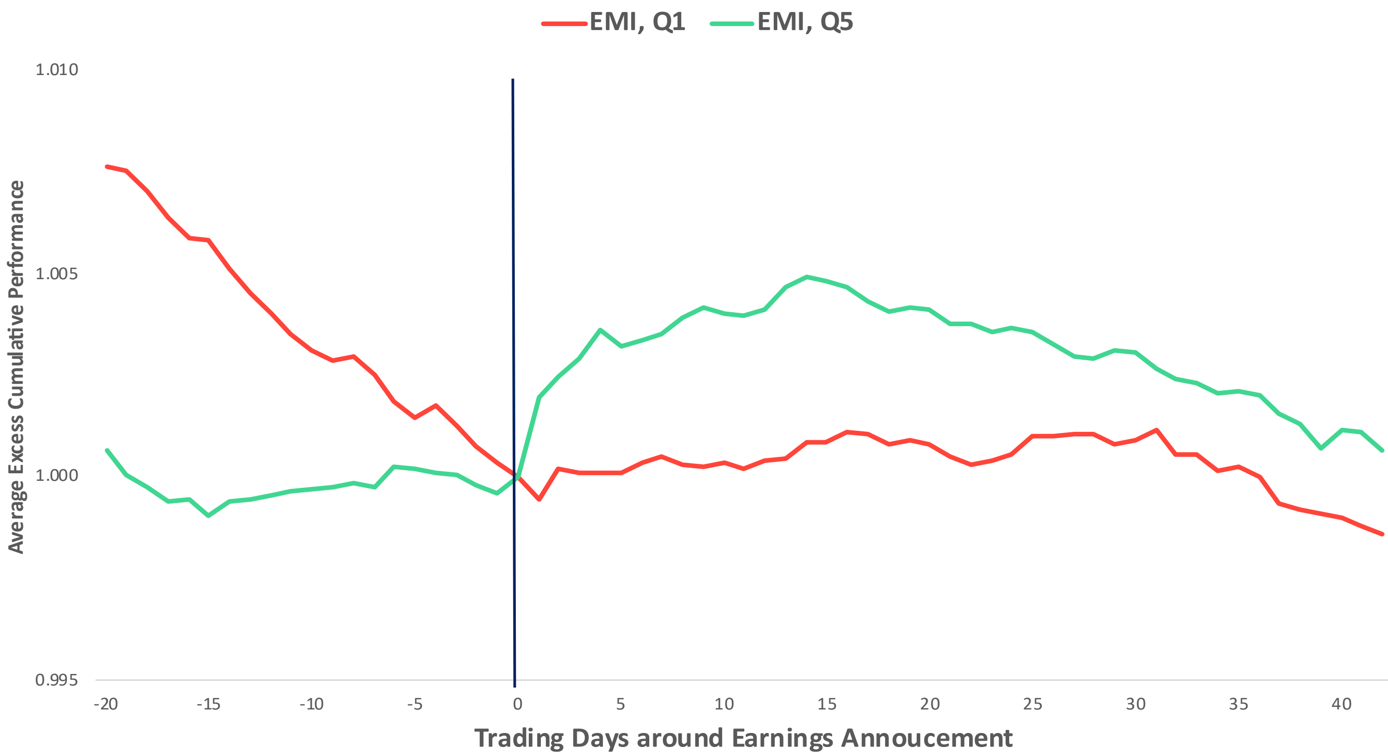


Sources: NewMark Risk, Bloomberg Finance LLP, MSCI, FTSE Russell, Markit, RavenPack, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

Earnings Surprise

Recall that the Emi is a systematic model that predicts earnings surprise, i.e., companies that are likely to beat and miss consensus earnings. As shown in Figure 7, companies with the largest risk of missing earnings (largest probabilities of beating earnings) tend to underperform (outperform) their peers both before and after earnings announcements.

Figure 7 Performance around Earnings Announcement, Predicted Earnings Surprise (by the EMI Model)



Sources: NewMark Risk, Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

Options-Based Signals

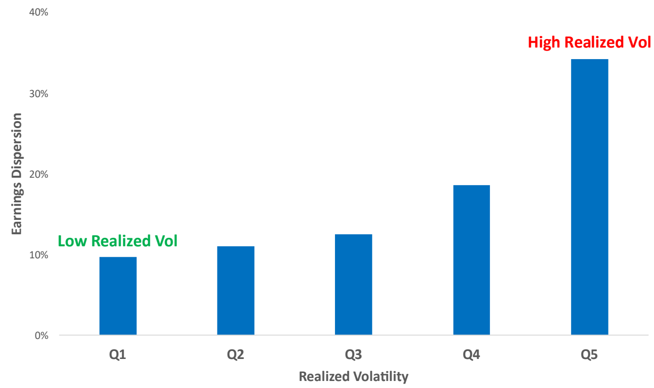
Among the few volatility-risk related signals, realized volatility and earnings dispersion are clearly correlated (see Figure 8A). Stocks with the highest realized volatilities (in Q5) suffer from much larger estimate dispersion than companies with the lowest realized volatilities (in Q1). As expected, firms with less predictable earnings (i.e., larger estimate dispersion) also tend to riskier, and vice versa.

In a similar vein, we observe that stocks with high earnings uncertainty (as well as EIV) also exhibit substantial analyst disagreement (see Figure 8B). Risker names often present greater alpha opportunities, attracting speculative attention, whereby analyst opinions can differ significantly. Additionally, volatile stocks tend to be particularly sensitive to market and economic conditions, especially in relation to their earnings reports.

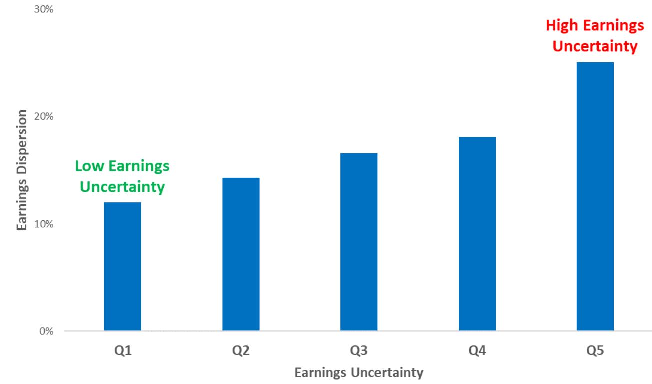
On the other hand, options-based sentiment (i.e., IV spread) and the EVRP (i.e., the spread between EIV and realized volatility) appear to be more orthogonal to earnings dispersion, offering fresh new insights.

Figure 8 Earnings Dispersion and Volatility

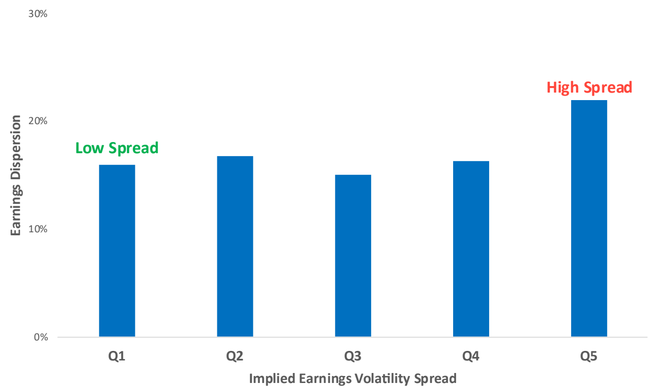
A) Avg Earnings Dispersion, by Realized Vol Quintiles



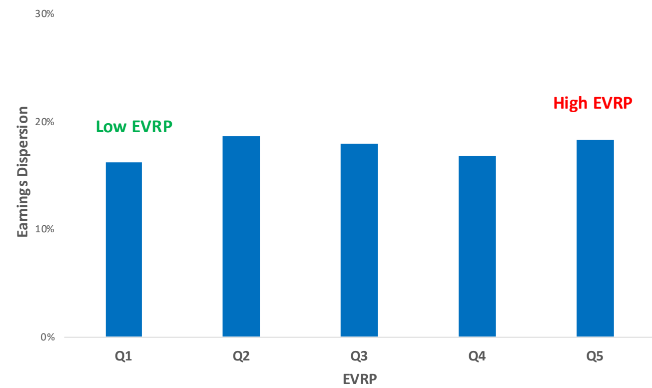
B) Avg Earnings Dispersion, by Earnings Uncertainty Quintiles



C) Avg Earnings Dispersion, by IV Spread Quintiles



D) Avg Earnings Dispersion, by EVRP Quintiles

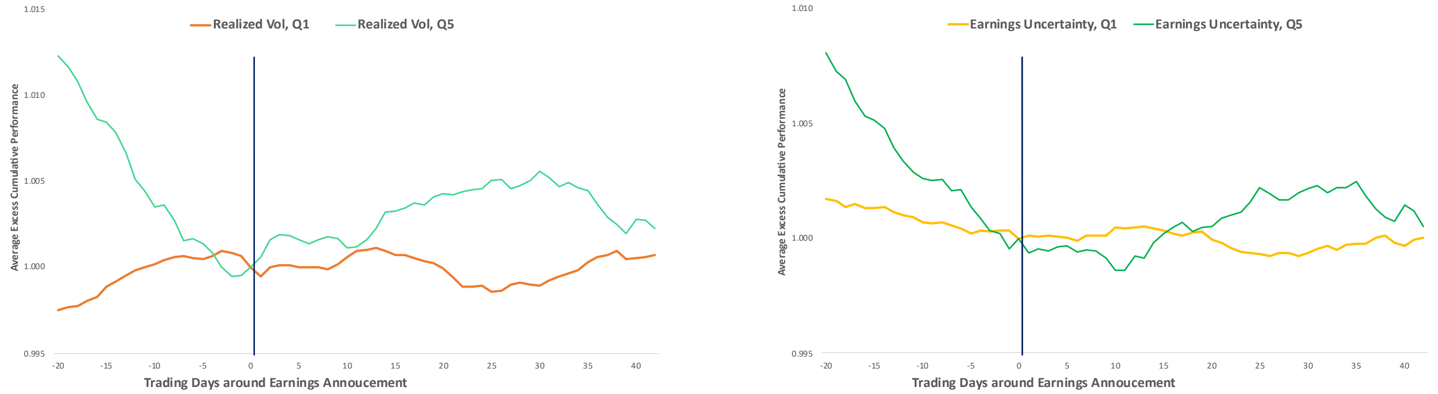


Sources: NewMark Risk, Bloomberg Finance LLP, MSCI, FTSE Russell, Markit, RavenPack, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

Empirically, investors seem to punish stocks with high realized volatility leading up to earnings announcement. However, once uncertainty around earnings is settled, these stocks actually recover some of their earlier losses post earnings releases (see Figure 9A). On the other hand, our earnings uncertainty (and EIV) model is better at capturing the post-earning announcement drift, in that firms with the largest earnings risk (in Q5) both before and immediately after earnings news (see Figure 9B).

Figure 9 Performance around Earnings Announcement, Realized Vol and Earnings Uncertainty

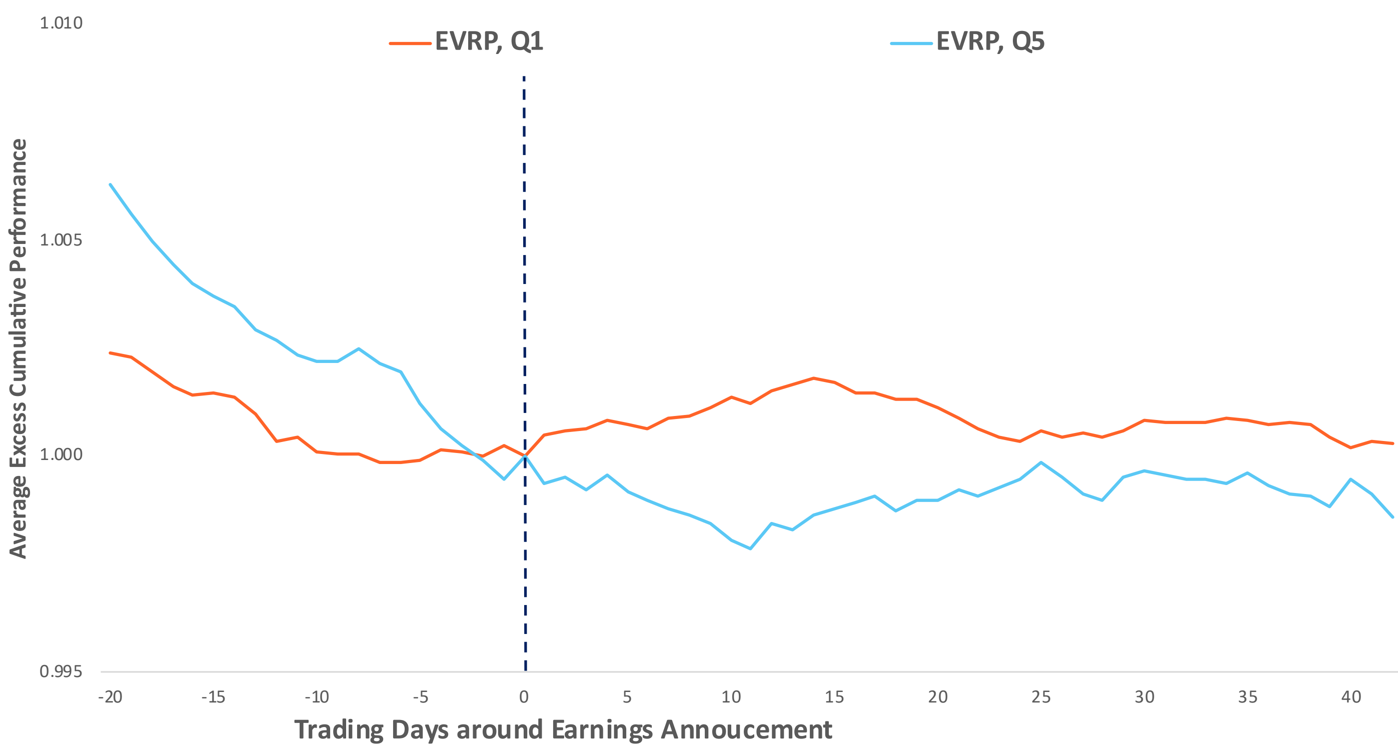
A) Realized Volatility **B) Earnings Uncertainty**



Sources: NewMark Risk, Bloomberg Finance LLP, MSCI, FTSE Russell, Markit, RavenPack, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

The most promising signal that is able to capture downside earnings risk seems to be the EVRP – the spread between EIV and realized volatility (see Figure 10). On average, options investors are better at predicting earnings risk – stocks with larger earnings-induced risk (as proxied by the EIV) than the stock market (i.e., realized volatility) tend to underperform their peers both prior to and after earnings announcements.

Figure 10 Performance around Earnings Announcement, EVRP



Sources: NewMark Risk, Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

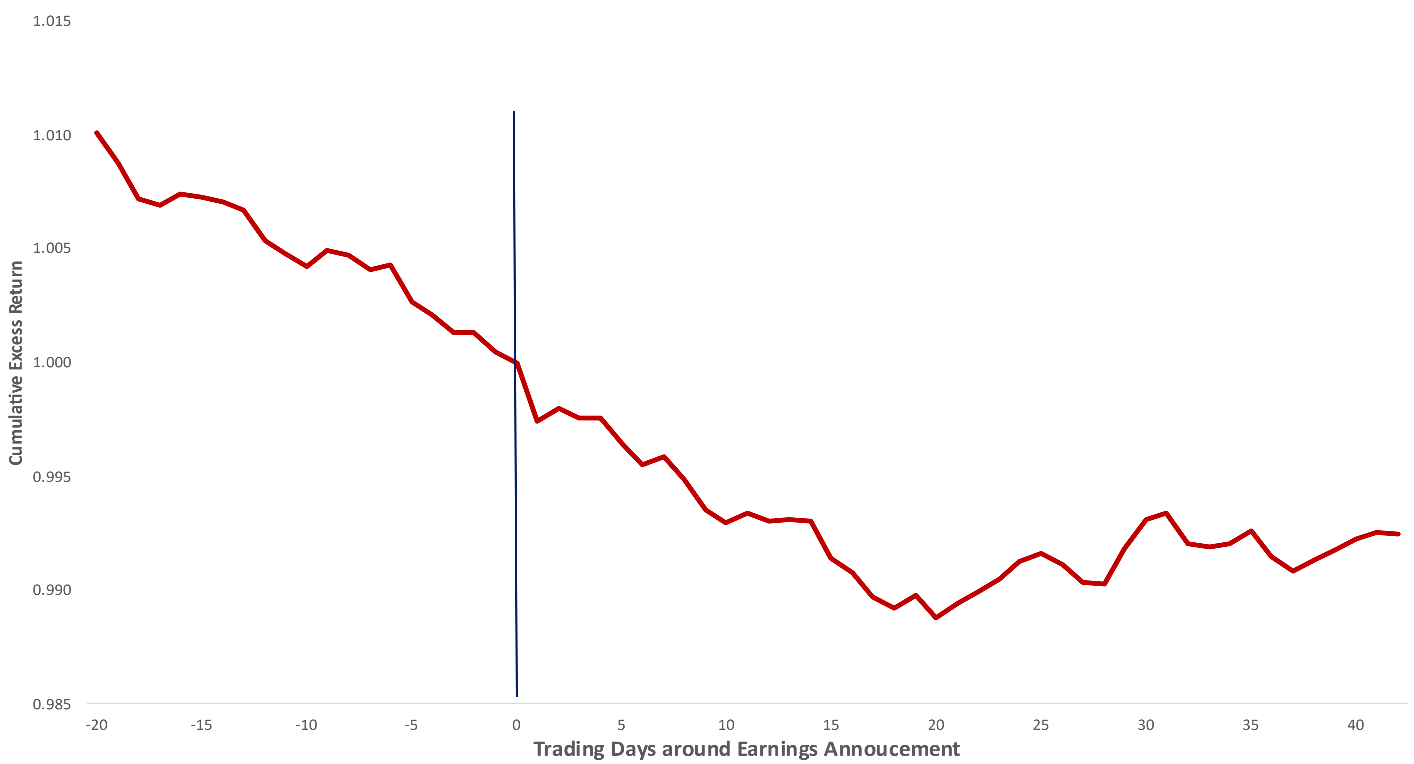
Introducing the Erie – Earnings Risk Prediction Model

To assist investors to identify shorting candidates or hedge out earnings risk, we put together the Erie screen, based on the following rules:

- First, we conduct an independent double sort to capture companies with the slowest near-term growth expectations (using the FQ1 consensus growth prediction factor) and highest (mispriced) earnings risk (using the EVRP signal, i.e., the largest earnings risk implied by the options market relative to the equity market prediction).
- Next, we add an additional filter of stocks with the highest probability of missing their consensus earnings expectations using the Emi model (in the bottom half of the universe).

As shown in Figure 11, stocks in the Erie model underperforms the market consistently, both prior to and after earnings announcement date. The optimal investor horizon is around a two-month window – one month before and one month after earnings date.

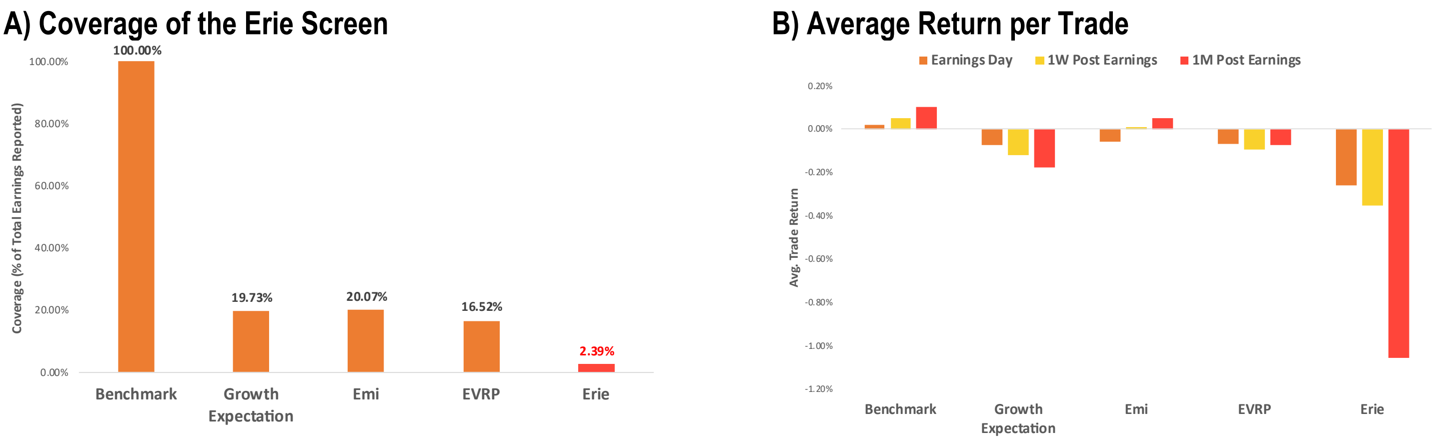
Figure 11 Performance around Earnings Announcement, the Erie



Sources: NewMark Risk, Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

As shown in Figure 12(A), each one of our three filters cuts down the number of companies in the screen by about 80%. The combined Erie screen focuses on a concentrated portfolio of around 20 companies with the largest earnings risk that is likely to be underpredicted by the market. By integrating near-term growth expectations, options-implied earnings-specific risk (i.e., the EVRP), and the systematic Emi model, we can effectively identify shorting candidates (see Figure 12B). Each one of the three filters enhances the performance of the Erie strategy. Moreover, given the strong diversification benefit, the basket tracked by the combined Erie model delivers an unannualized return of more than 1% in the month post earnings announcement[1].

Figure 12 Performance Comparison based on Event Study (December 2012 – Present)



Sources: NewMark Risk, Bloomberg Finance LLP, MSCI, FTSE Russell, Markit, RavenPack, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

The Erie Screen

Currently, we provide the Erie screen on a daily basis and highlight companies with the largest unexpected earnings risk. Because our goal is to capture near-term earnings uncertainty, we focus on firms that are expected to release earnings in the next two months.

- Earnings uncertainty[2] (i.e., predicted price movement due to earnings risk)
- Average PMIE[3] (i.e., trailing three-year average absolute daily return on the earnings day)
- Last realized PMIE[4] (i.e., absolute daily return on the last quarter's earnings day)
- EVRP[5] (i.e., the spread between EIV and realized volatility)
- Option sentiment[6] (i.e., IV Spread)
- Erie short flag[7] (potential short candidates by the Erie)
- Wolfe analyst rating (OutPerform-OP, PeerPerform-PP, UnderPerform-UP)

[1] Again, as a reminder, the Erie is a short basket.
[2] Earnings uncertainty measures the predicted price movement due to earnings risk, using options IV curve.
[3] Avg PMIE (Price Movement Induced by Earnings) is the trailing three-year average absolute daily return on the earnings day.
[4] Last PMIE (Price Movement Induced by Earnings) is the absolute daily return on the last quarter's earnings day.
[5] EVRP (Earnings Volatility Risk Premium) – the spread between earnings-induced volatility (from options market) and realized volatility – measures the potential mispricing between options and equity markets.
[6] IV spread is the difference between ATM call and put options.
[7] Short Flag is based on the Erie model (i.e., stocks with the slowest expected earnings growth, highest earnings risk, and highest probability of missing earnings expectations).

Figure 13 Current Erie Screen, Top 30 Names

Tticker	Company Name	Sector	Industry	Earnings Date	Earnings Uncertainty	Avg PMIE	Last realized PMIE	EVRP	Option Sentiment	Erie Short Flag	Wolfe Analyst Rating
NOW	ServiceNow Inc	Information Technology	Software	1/23/24	2.6%	5.4%	4.4%	0.5%	2%		
APH	Amphenol Corp	Information Technology	Electronic Equipment, Instruments & Components	1/23/24	2.4%	2.2%	0.5%	0.6%	-2%		
SF	Stifel Financial Corp.	Financials	Capital Markets	1/23/24	2.3%	3.4%	5.2%	0.6%	3%		OP
KNX	Knight-Swift Transportation Holdings Inc	Industrials	Road & Rail	1/23/24	3.2%	3.1%	11.7%	-0.6%	0%		OP
LRCX	Lam Research Corp	Information Technology	Semiconductors & Semiconductor Equipment	1/23/24	2.9%	4.6%	6.3%	-3.2%	-1%		
WRB	Berkley (W.R.) Corp	Financials	Insurance	1/23/24	2.7%	3.2%	6.2%	2.7%	-38%		
NSC	Norfolk Southern Corp	Industrials	Road & Rail	1/23/24	1.5%	2.2%	5.3%	-2.8%	2%		OP
KLAC	KLA Corp	Information Technology	Semiconductors & Semiconductor Equipment	1/23/24	2.2%	4.2%	0.7%	-3.0%	3%		
CACI	CACI International Inc	Industrials	Professional Services	1/23/24	2.6%	3.4%	1.5%	1.4%	8%		
FFIV	F5 Inc	Information Technology	Communications Equipment	1/23/24	2.4%	5.6%	2.3%	1.3%	-2%		
TSLA	Tesla Inc	Consumer Discretionary	Automobiles	1/23/24	2.6%	7.0%	9.3%	0.5%	-1%		
HXL	Hexcel Corp	Industrials	Aerospace & Defense	1/23/24	2.9%	4.2%	7.7%	1.7%	-5%		
MMM	3M Co	Industrials	Industrial Conglomerates	1/23/24	2.0%	2.7%	5.3%	0.0%	-2%		
GD	General Dynamics Corp	Industrials	Aerospace & Defense	1/23/24	0.7%	1.6%	4.0%	-1.5%	-10%		
TXT	Textron Inc	Industrials	Aerospace & Defense	1/23/24	2.9%	3.8%	2.2%	-0.1%	0%		PP
SHW	Sherwin-Williams Co (The)	Materials	Chemicals	1/24/24	2.7%	3.6%	1.5%	0.7%	6%		
MKC	McCormick & Co Inc	Consumer Staples	Food Products	1/24/24	3.4%	3.9%	8.5%	2.3%	3%		
BPOP	Popular Inc	Financials	Banks	1/24/24	2.7%	4.2%	7.7%	0.3%	-2%		
MMC	Marsh & McLennan Companies Inc	Financials	Insurance	1/24/24	1.1%	2.4%	0.7%	0.3%	-21%		
DOW	Dow Inc	Materials	Chemicals	1/24/24	1.0%		0.0%	-0.3%	-3%		
WY	Weyerhaeuser Co	Real Estate	Specialized REITs	1/24/24	4.1%	2.2%	1.3%	2.1%	-2%		
NEE	NextEra Energy Inc	Utilities	Electric Utilities	1/24/24	1.9%	3.9%	7.0%	-0.4%	-3%		
FCX	Freeport-McMoRan Inc	Materials	Metals & Mining	1/24/24	2.1%	3.4%	1.1%	-3.6%	0%		
CBSH	Commerce Bancshares Inc	Financials	Banks	1/24/24	6.5%	2.1%	2.1%	3.7%	18%	TRUE	
PII	Polaris Inc	Consumer Discretionary	Leisure Products	1/24/24	3.8%	3.9%	2.7%	1.8%	1%		
ALK	Alaska Air Group Inc	Industrials	Airlines	1/24/24	2.8%	2.1%	1.5%	-3.1%	-3%		
MKSI	MKS Instruments Inc	Information Technology	Semiconductors & Semiconductor Equipment	1/24/24	1.5%	3.9%	0.5%	-3.4%	2%		
OLN	Olin Corp	Materials	Chemicals	1/24/24	3.3%	5.1%	9.0%	1.5%	12%		
AXTA	Axalta Coating Systems Ltd	Materials	Chemicals	1/24/24	3.6%	3.6%	8.1%	2.3%	0%		
SLGN	Silgan Holdings Inc	Materials	Containers & Packaging	1/24/24	3.4%	4.3%	5.8%	2.0%	5%		
COF	Capital One Financial Corp.	Financials	Consumer Finance	1/24/24	2.3%	4.6%	9.2%	-0.8%	0%		

Sources: NewMark Risk, Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

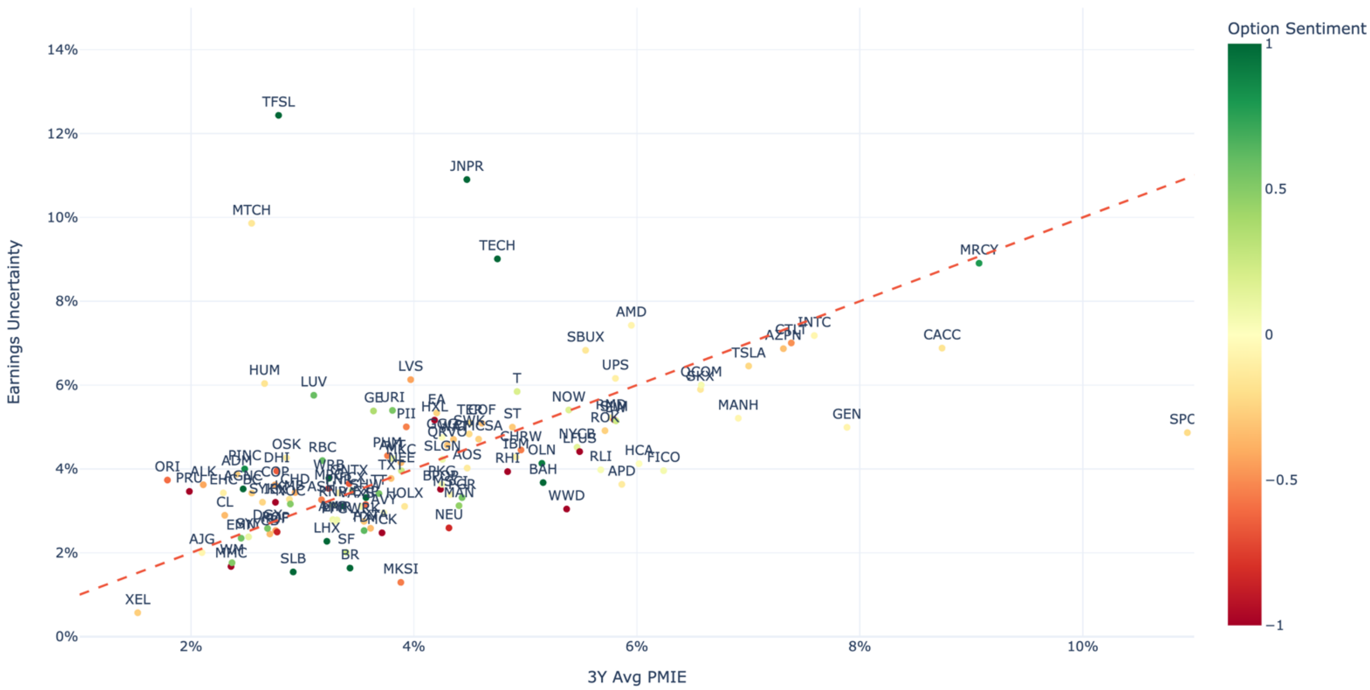
Predicted versus Realized Earnings Uncertainty

Next, we would like to understand the discrepancy between the implied earnings risk by the options market (i.e., our earnings uncertainty measure) versus historical realized earnings-induced price fluctuation (i.e., trailing three-year average PMIE), as shown in Figure 14.

- Companies in the upper left-hand corner above the trend line are those where options investors assign a higher level of earnings risk than equity investors (or historical realized price movement).
- Points in the lower right-hand side below the trend line indicate those firms where options market might "underpredict" near-term earnings risk relative to historical averages.

This analysis supplements our quantitative screen, providing an additional perspective and highlighting potentially "overpredicted" or "underpredicted" earnings risk. From Figure 14, there are clearly far more companies in the upper left-hand corner than in the bottom right-hand area, suggesting that options investors on average overestimate earnings risk – a potential problem that we will address in the next section.

Figure 14 The Discrepancy between Options and Equity Markets (Current)



Sources: NewMark Risk, Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

Incorporating Earnings Uncertainty in Portfolio Construction

In the last section, we demonstrate how to incorporate earnings uncertainty in the portfolio construction process. Multifactor equity risk models used to be exclusively adopted by only quantitative portfolio managers. However, in recent years, we have seen a rapid adoption by fundamental and discretionary managers. Commercial risk models do not take into account the idiosyncratic nature of earnings uncertainty. In this section, we construct a custom risk model – the Erie-Risk – that incorporate both traditional risk factors and earnings uncertainty. We find that the Erie-Risk boosts the accuracy of our baseline Wolfe QES Standard Risk Model considerably, especially on the idiosyncratic component and particularly during earnings season. The Erie-Risk not only enjoys high statistical accuracy, but also leads to active portfolios with higher Sharpe ratio (IR), lower realized volatility and downside risk. For managers who do not use mean-variance portfolio optimizer, they can easily apply the Erie-Risk to construct custom hedges against the unintentional/undesirable earnings uncertainty risk.

The Baseline Risk Model

Starting from our baseline QES Standard Risk Model, we first re-fit the model for our US large-cap investment universe. It is worth highlighting that our custom risk model engine offers the flexibility to re-fit the risk model for any specific investment universe, risk factors, correlation structure, and idiosyncratic risk estimation easily.

On a high level, our risk model is estimated as follows (details can be found in *Port@ble Ownership*, Alvarez, et al [2018]):

$$\boldsymbol{r} = \boldsymbol{Xf} + \boldsymbol{\varepsilon}$$

Where,

$\boldsymbol{r}$ is the $(N \times 1)$ vector stock returns,

$\boldsymbol{X}$ is the $(N \times K)$ matrix of factor exposures,

$\boldsymbol{f}$ is the $(K \times 1)$ vector of factor returns,

$\boldsymbol{\varepsilon}$ is $(N \times 1)$ vector idiosyncratic returns,

N is the number of stocks in the risk model, and

K is the number of risk factors.

Based on a multifactor risk model, the asset-level (stock) risk forecast $\boldsymbol{\Sigma}_t^{RM}$ generated at time t can be represented as:

$$\boldsymbol{\Sigma}_t^{RM} = \boldsymbol{XFX}' + \boldsymbol{\Lambda}$$

Where,

$\boldsymbol{\Sigma}_t^{RM}$ is the $(N \times N)$ stock-by-stock variance-covariance matrix,

$\boldsymbol{F}$ is the $(K \times K)$ factor covariance matrix, estimated using the factor return vector $\boldsymbol{f}$, and

$\boldsymbol{\Lambda}$ is the $(N \times N)$ diagonal matrix of stock-specific idiosyncratic volatility, based on the idiosyncratic return vector $\boldsymbol{\varepsilon}$.

Introducing the Bias Statistic on Idiosyncratic Risk (BSIR)

We see earnings uncertainty as part of firm-specific idiosyncratic news rather than systematic common factor risk. Therefore, in this section, we focus on the idiosyncratic volatility component $\boldsymbol{\Lambda} = \{\sigma_i^{Idio}\}_{\boldsymbol{i=1}}^{\boldsymbol{n}}$. To assess the accuracy of our idiosyncratic risk prediction, we need to introduce a new concept called BSIR (Bias Statistic on Idiosyncratic Risk).

In assessing the precision of a risk model, we use the widely recognized Bias Statistic metric (Mueller et al [1993]). As explained in Mueller et al [1993] and *Risk Model Deep Dive – Forecasting Correlation*, (see Elledge, et al [2022]), the bias statistic is widely used in the risk model literature to measure the overall accuracy of a risk model's ability to predict risk at the portfolio level. An accurate risk model should have a long-term average bias statistic close to one. A bias statistic above (below) one means that the risk has underpredicted (overpredicted) risk.

We introduce the BSIR metric to specifically assess a risk model's accuracy in estimating the idiosyncratic risk component.

If we assume portfolio return is normally distributed with a mean of μ and a standard deviation of σ, i.e., $r \sim N(\mu\,,\sigma^2)$, we can derive $r/\sigma \sim N(\mu/\sigma\,,1)$. Assuming a perfect volatility forecast, the standard deviation of (r/σ) should equate to 1. Let us first define:

[E1] $$Bias_{p,t} = \frac{r_{p,t}}{\sigma_{p,t}}$$

Where,

$r_{p,t}$ is the historical (realized) active return of portfolio p at time t, and

σ_p is *ex ante* (predicted) volatility of portfolio p at time t.

Assuming a perfect risk forecast of σ_p, we can derive:

[E2] $$BiasStatistic_{p,t} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(Bias_{p,t} - \overline{Bias_p}\right)} = 1$$

We can further assume that the expected idiosyncratic return is zero. Then, we define our BSIR. At the start of the time t, we define the specific cross-sectional bias statistic on time t as:

[E3] $$BSIR_t = \sqrt{\frac{1}{N}\sum_i\left(\frac{\varepsilon_{i,t}}{\sigma_{i,t}^{Idio}}\right)^2}$$

Where, $\varepsilon_{i,t}$ is the idiosyncratic return for stock i at time t, and

$\sigma_{i,t}^{Idio}$ is the estimated idiosyncratic volatility for stock i at time t.

The BSIR measure can be computed using all stocks in our investment universe at each point-in-time. The long-term average BSIR should be close to unity. Similar to how we interpret the bias statistic, if the BSIR is above (below) one, our risk model has underpredicted (overpredicted) stock-specific risk.

Idiosyncratic Volatility around Earnings Announcement

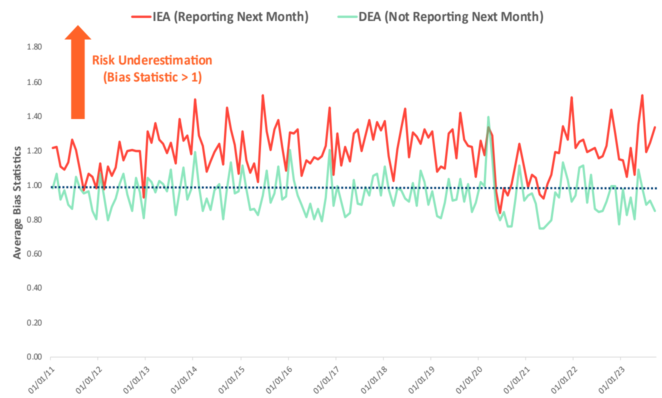
To understand whether our baseline risk model systematically underestimate earnings uncertainty, we splits companies in our investment universe based on the horizon of the next earnings reporting date:

- IEA (Imminent Earnings Announcement) Group: companies that are scheduled to release earnings in the next calendar month; and
- DEA (Distant Earnings Announcement) Group: firms that are not expected to report earnings in the following month

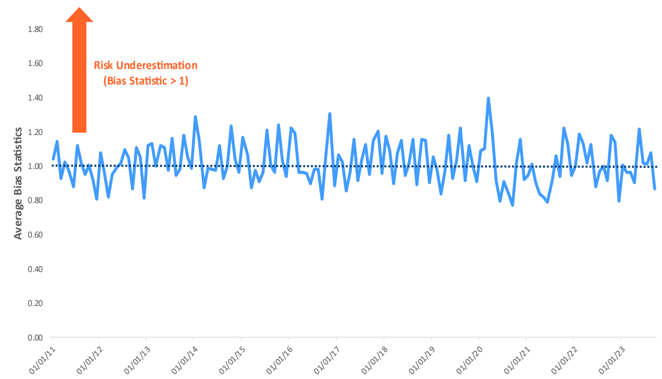
As shown in Figure 15(A), the realized BSIR for companies with pending earnings announcement (i.e., the IEA group) is materially higher than for the control group (i.e., the DEA group). Overall, the QES risk models provide an accurate idiosyncratic risk forecast with the long-term average BSIR close to one (see Figure 15B).

Figure 15 Realized BSIR

A) Underestimation of Earnings Risk



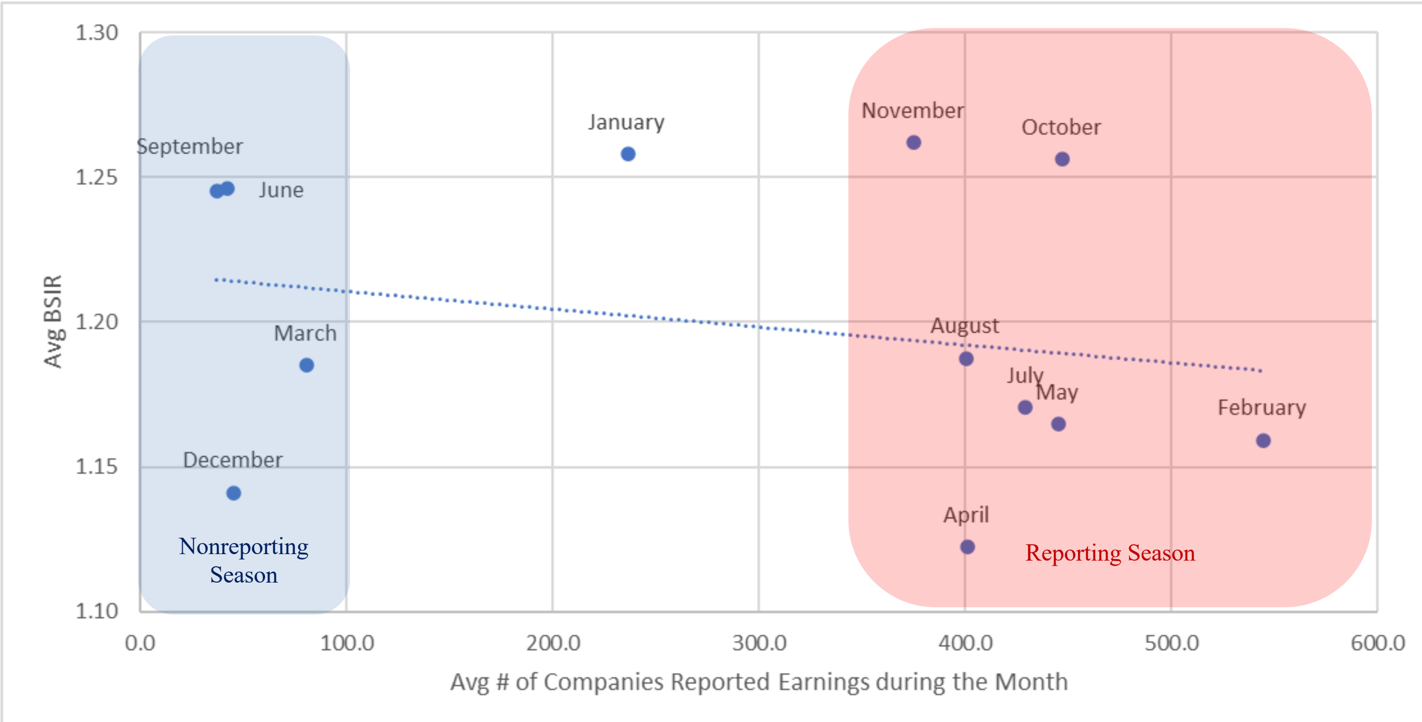
B) Overall Bias Statistic



Sources: NewMark Risk, Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

If we plot the number of companies reported earnings against the BSIR, we see interesting seasonal patterns (see Figure 16). Our risk models tend to underestimate earnings-induced risk during non-reporting months when fewer companies report earnings, i.e., when sample size is small, albeit results are not statistically significant.

Figure 16 BSIR versus Reporting Season



Sources: NewMark Risk, Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

Introducing the Erie-Risk

For portfolio managers who are not willing to take on company-specific earnings risk, it is desirable to take earnings uncertainty into account in the risk model.

Following *Combining Views from Multiple Sources* (see Elledge, et al [2022]), we utilize a Bayesian shrinkage method to incorporate earnings uncertainty into the existing idiosyncratic volatility component from the Wolfe QES Standard Risk Model. We label the enhanced risk model as Erie-Risk.

The Bayesian Shrinkage Framework – A Short Introduction

The Bayesian shrinkage estimation process updates prior beliefs using observed sample data. In a Bayesian framework, shrinkage is achieved by combining prior beliefs with the likelihood of observing the data, resulting in a posterior estimation. To estimate the parameter set $\boldsymbol{\theta}$, given observed data $\boldsymbol{X}$, the Bayes' theorem conducts the following transformation:

$$P(\boldsymbol{\theta}|\boldsymbol{X}) \propto P(\boldsymbol{X}|\boldsymbol{\theta}) \cdot P(\boldsymbol{\theta})$$

Where,

$P(\boldsymbol{\theta})$ is the prior probability of the parameters,

$P(\boldsymbol{X}|\boldsymbol{\theta})$ is the likelihood of observing the data given the parameters, and

$P(\boldsymbol{\theta}|\boldsymbol{X})$ is the posterior probability of the parameters given the data.

Assuming both the prior distribution for $\boldsymbol{\theta}$ and the sample data $\boldsymbol{X}$ given $\boldsymbol{\theta}$ are normally distributed such that:

$$\boldsymbol{\theta} \sim \mathcal{N}\left(\boldsymbol{\mu}, \boldsymbol{\sigma}_{prior}^2\right)$$

$$\boldsymbol{X}|\boldsymbol{\theta} \sim \mathcal{N}(\boldsymbol{\theta}, \boldsymbol{\sigma}_{likelihood}^2)$$

Using Bayes' theorem, the posterior distribution $P(\boldsymbol{\theta}|\boldsymbol{X})$ also follows a normal distribution, due to the conjugate nature of the normal distribution. The mean of the posterior distribution, $\widetilde{\boldsymbol{\mu}}$, can be calculated as a weighted average of the prior mean and the population mean $\boldsymbol{X}$ (unknown) as:

$$\widetilde{\boldsymbol{\mu}} = (1-\lambda)\boldsymbol{X} + \lambda\boldsymbol{\mu}$$

Here, λ is the shrinkage parameter that determines the weighting of the prior mean and is defined as:

$$\lambda = \frac{\boldsymbol{\sigma}_{likelihood}^2}{\boldsymbol{\sigma}_{likelihood}^2 + \boldsymbol{\sigma}_{prior}^2}$$

In real world applications, we use the sample mean $\overline{\boldsymbol{X}}$ to replace $\boldsymbol{X}$ and sample variance to replace $\boldsymbol{\sigma}_{prior}^2$ and $\boldsymbol{\sigma}_{likelihood}^2$, to approximate the posterior mean $\widetilde{\boldsymbol{\mu}}$.

Prior Estimate of Idiosyncratic Volatility

The Wolfe QES risk models take into account style, sector/industry, and other systematic risk factors, along with sophisticated algorithms to estimate stock-specific volatility. However, as detailed in the previous sections, our risk models (similar to other commercial risk models) do not explicitly incorporate company-specific earnings uncertainty – risk models typically treat earnings news as part of idiosyncratic risk. On the other hand, options investors pay particular attention to earnings news, but typically do not use multifactor equity risk models, leading to an overestimation of idiosyncratic volatility (see Figure 14 for some anecdote evidence). Therefore, it is intuitive to construct our prior view on idiosyncratic risk by mixing these two. It is important to note that the prior is a crude way of combining these two models, but it offers a reasonable starting point.

$$\boldsymbol{\sigma}_{Prior}^{Idio} = \sqrt{(\sigma_{Sample}^{Idio})^2 + (\boldsymbol{\sigma}_{EIV}^{Idio})^2}$$

Where,

$\boldsymbol{\sigma}_{Prior}^{Idio}$ is our Bayesian prior estimate of idiosyncratic volatility,

σ_{Sample}^{Idio} is the *ex ante* idiosyncratic volatility from the baseline Wolfe Standard Risk Model, and

$\boldsymbol{\sigma}_{EIV}^{Idio}$ is the EIV factor discussed in the previous sections, i.e., options-implied earnings induced risk.

A Bayesian Combination of Risk Model Idiosyncratic Volatility and Options-Induced Earnings Risk

Next, we apply the Bayesian shrinkage method to blend prior view on idiosyncratic risk (defined in the previous paragraph), with observed data (i.e., our baseline risk model estimated idiosyncratic risk). The Bayesian posterior estimate $\widetilde{\boldsymbol{\sigma}}_{Bayesian}^{Idio}$ is computed as:

$$\widetilde{\boldsymbol{\sigma}}_{Posterior}^{Idio} = \left(1-\hat{\lambda}\right)\boldsymbol{\sigma}_{Sample}^{Idio} + \hat{\lambda}\,\boldsymbol{\sigma}_{Prior}^{Idio}$$

Where,

$\widetilde{\boldsymbol{\sigma}}^{Idio}_{Bayesian}$ is the Bayesian posterior estimate of idiosyncratic volatility, and

$\hat{\lambda}$ is the shrinkage parameter.

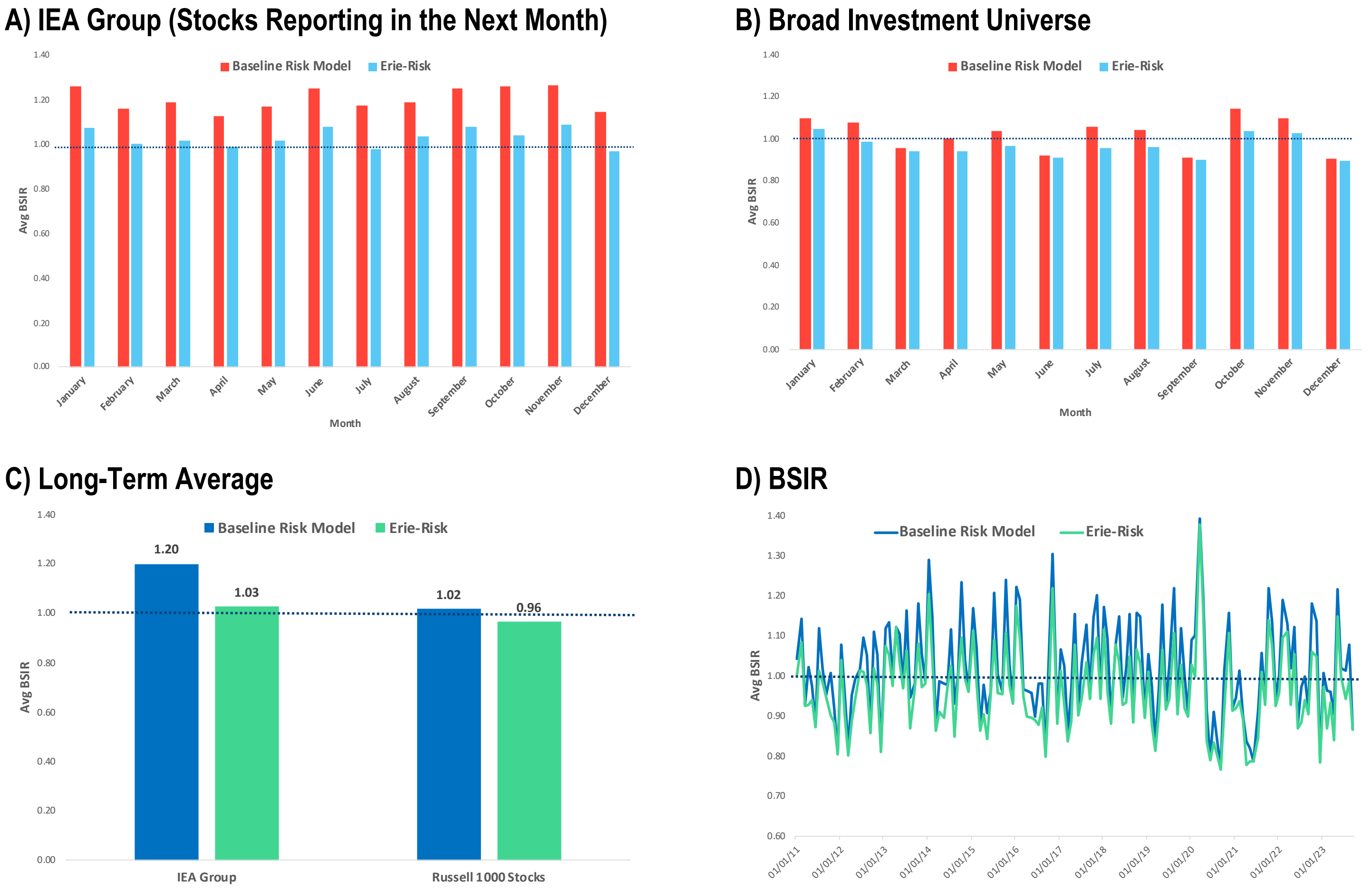
We use the rolling three-month mean squared error of our predicted idiosyncratic volatility against realized risk to approximate $\boldsymbol{\sigma}_{likelihood}$ and $\boldsymbol{\sigma}_{prior}$, which correspond to the weight assigned to sample data and prior, respectively. As a result, the more accurate component receives a higher weight in computing our posterior.

Evaluating the Erie-Risk

As shown in Figure 17(A), our baseline risk model underestimates idiosyncratic risk for all calendar months, especially for companies that are reporting earnings in the near term (i.e., the coming month). On the other hand, the Erie-Risk using options data and the Bayesian framework improves the accuracy of idiosyncratic volatility considerably, bringing the BSIR much closer to one.

Beyond companies with pending earnings announcements, our Erie-Risk model also boosts stock-specific risk estimates in general (see Figure 17B), albeit at a smaller magnitude (see Figure 17C). The improvement in idiosyncratic risk estimates is consistent over time, particularly during the COVID and post-COVID environment.

Figure 17 Performance of the Erie-Risk Model, BSIR



Sources: Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

Portfolio Construction Incorporating Earnings Uncertainty

As discussed in *Risk, Portfolio Construction, and Performance Attribution* (see Luo, et al [2017]), a more accurate risk model presumably better aligns a portfolio with its intended goals, leading to the bias statistic closer to one. However, we also know that statistical accuracy is different from economic benefit. Therefore, a better risk model does not necessarily mean better performance, e.g., Sharpe ratio or IR (see *Machine Learning in Risk Predictions*, Li, et al [2023]).

In this section, we detail how to incorporate earnings uncertainty in the portfolio construction process. More importantly, using a realistic portfolio, we demonstrate both improved statistical accuracy and better risk-adjusted performance with our enhanced Erie-Risk model. In the demonstration below, we use the MALTA – our flagship global stock-selection model – as the example to construct an active portfolio (see *Man versus Machine*, Wang, et al [2018] for details).

The Mean-Variance Portfolio Construction Framework

We assess the efficacy of the Erie-Risk using the mean-variance portfolio construction framework. Following the methodology outlined in *Risk, Portfolio Construction, and Performance Attribution* (see

Luo, et al [2017]), we set up the portfolio construction process with the following objective function:

$$argmax_{\boldsymbol{\omega}}(\boldsymbol{\omega}'\boldsymbol{\alpha} - \frac{\lambda}{2}\boldsymbol{\omega}'\boldsymbol{\Sigma}\boldsymbol{\omega})$$

Where,

$\boldsymbol{\omega}$ is a $(N \times 1)$ vector of stock weights – to be solved by the optimizer,

$\boldsymbol{\alpha}$ is a $(N \times 1)$ vector of expected returns (i.e., stock return forecast), using our MALTA model prediction,

$\boldsymbol{\Sigma}$ is a $(N \times N)$ variance-covariance matrix from a risk model (we compare portfolio performance using our baseline Wolfe Standard Risk Model and the Erie-Risk), and

λ is the risk aversion parameter (typically calibrated to fit a target risk level).

Real-life portfolios face multiple constraints. Following *Premium Quality Risk Premia* (see Wang, et al [2024]), we set the following constraints in the optimizer:

- Investment universe is the point-in-time Russell 1000 index constituents
- Long/short market neutral and dollar neutral with 2x leverage
- Notional AUM: $100 million
- Maximum single stock absolute weight of 3%
- At each rebalance, we cannot trade more than 10% ADV (Average Daily Volume) of any stock
- Hard-to-borrow stocks are excluded from the short side
- Monthly rebalancing frequency
- Portfolio is simulated from December 2010 onwards

For comparison purposes, we construct our active MALTA portfolio using each of the two risk models (baseline and enhanced), respectively, with identical setup.

Risk Model Statistical Accuracy

First, we assess the statistical accuracy of the two risk models using the bias statistic defined in the previous section. Specifically, at time t, the contemporaneous portfolio bias statistics is computed as the ratio of *ex post* monthly risk σ_t^{Port} over the *ex ante* predicted risk $\hat{\sigma}_t^{Port}$ (generated at time $t-1$):

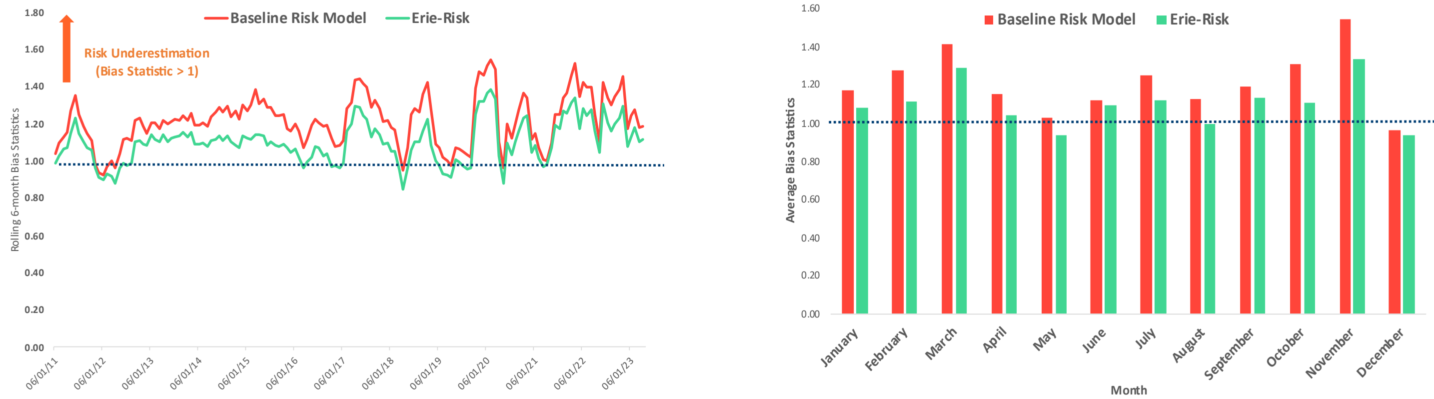
$$BiasStatistic_t^{Port} = \frac{\sigma_t^{Port}}{\hat{\sigma}_t^{Port}}$$

Realized monthly volatility σ_t^{Port} is calculated using the portfolio's daily returns within month t. We use the rolling six-month moving average of $BiasStatistic_t^{Port}$ as our primary metric to assess the portfolio.

Mueller et al [1993] and *Risk Model Deep Dive – Forecasting Correlation* (see Elledge, et al [2022]) show that risk models often underestimate risk. As shown in Figure 18(A), realized bias statistic for the MALTA portfolio using our baseline risk model is consistently higher than one most of time, meaning that our risk model underestimates risk on average, particularly at the onset of the COVID crisis. The improvement from the Erie-Risk is highly significant – the realized bias statistic is much closer to one. The enhancement is particularly strong during earnings season in February, April, July, and October (see Figure 18B). Incorporate earnings uncertainty (from options data) with our Bayesian framework leads to more accurate risk prediction and portfolios better aligned with intended purposes.

Figure 18 Comparing the Baseline Risk Model and Erie-Risk, MALTA Portfolio

A) Bias Statistic **B) Bias Statistic, By Month**

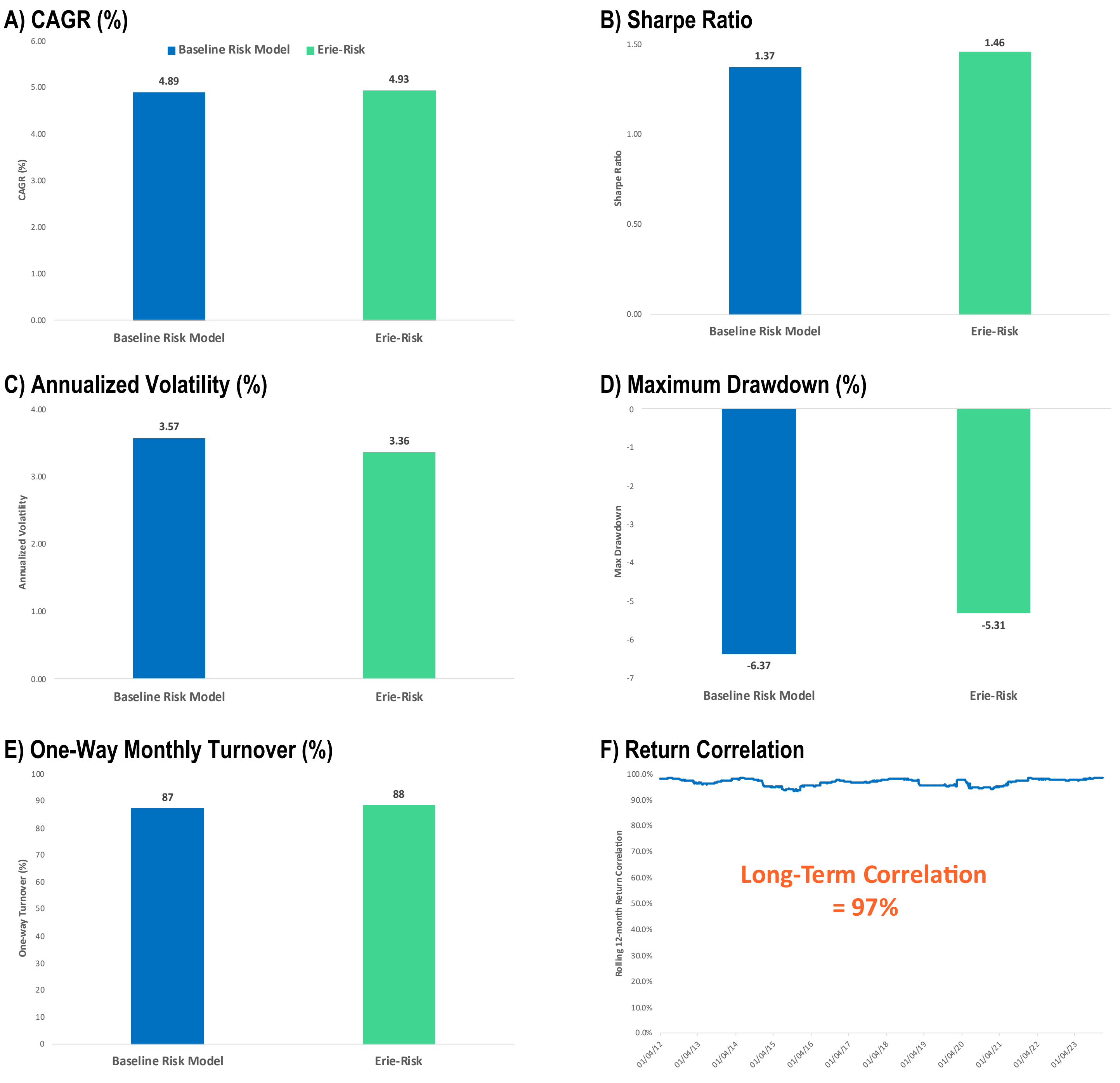


Sources: NewMark Risk, Bloomberg Finance LLP, MSCI, FTSE Russell, Markit, RavenPack, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

Portfolio Performance

As shown in Figure 19, the MALTA portfolio constructed using the Erie-Risk model delivers higher return (see Figure 19A), better Sharpe ratio (see Figure 19B), lower volatility (see Figure 19C), and materially lower downside risk (see Figure 19D). The turnover of the portfolio stays the same (see Figure 19E). The returns of portfolios constructed using the two risk models are also highly correlated, with a long-term average correlation close to 97% (see Figure 19F).

Figure 19 Portfolio Performance Comparison, Baseline Risk Model versus the Erie-Risk

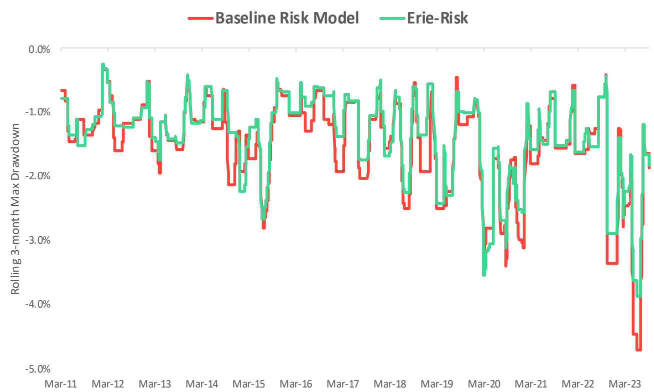


Sources: NewMark Risk, Bloomberg Finance LLP, MSCI, FTSE Russell, Markit, RavenPack, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

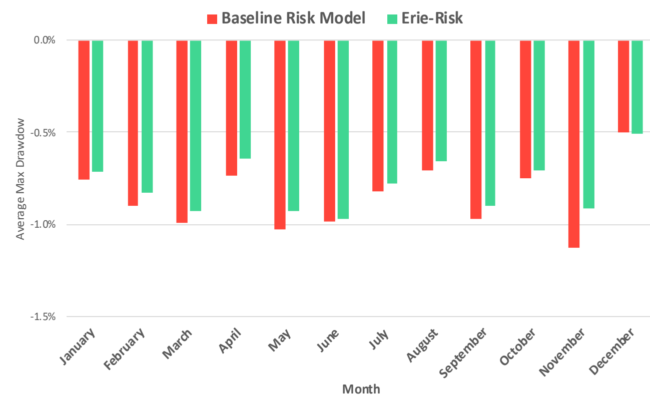
Because earnings uncertainty is one of the most significant sources of idiosyncratic risk, we would expect material reduction of tail risk by incorporating the Erie-Risk model. As shown in Figure 20(A), the improvement in downside risk with the Erie-Risk is significant, particularly at market turning points such as Q4/2023 (the risk rally triggered by Fed rate expectations). Figure 20 shows the timeseries maximum drawdown. The mitigation of downside risk is especially pronounced during peak earnings season such as February, April, and November (see Figure 20B).

Figure 20 Improvement in Downside Risk Reduction

A) Rolling Three-Month Maximum Drawdown



B) Average Maximum Drawdown, by Month



Sources: NewMark Risk, Bloomberg Finance LLP, FTSE Russell, MSCI, Refinitiv, S&P Capital IQ, S&P Trucost, Wolfe Research Luo's QES

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